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Employment Polarization and the Role of the Apprenticeship System[*]

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Abstract

This paper studies the effect of apprenticeship training on technology adoption and labor market polarization. A stylized model with two key features is developed: (1) apprentices are more productive due to industry-specific training, but (2) from the firm's perspective, when training apprentices, technological innovation is costly since training becomes obsolete. Thus, apprentices correlate with slower adoption of skill-replacing technologies, but also less employment polarization. We test this hypothesis on German regions given local variation in apprenticeship systems until 1976. The results show little computer adoption and no employment polarization related to apprentices, but similar displacement of non-apprentices by computers as in the US.

JEL classification: E24, J24, O33, R23

Keywords: Apprentices, educational system, employment polarization, technology adoption

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1 Introduction

One of the most significant changes in the labor market has been the increasing adoption of computer technology since the 1970s. Recent research has highlighted one specific impact of this information and communications technology (ICT) innovation: the displacement of middle-wage employment by capital. Autor et al. (2003) first documented the effect of computers, not only complementing the high-skilled, but replacing middle-skilled jobs in the US. The study suggests that computers most easily replace routine tasks.[1] As employment polarization is present in both the US and Germany (see Figure 1a), it seems natural to conjecture that both countries experienced technical change in ICT related to the replacement of middle-skill employment. However, graphing the share of employment using computers at work in 1999 against the share of routine-intensive employment in 1979 across German labor market regions (see Figure 1b) presents a puzzle in terms of the employment polarization hypothesis. German regions with the lowest routine employment share in 1979 have the highest per worker computer usage in 1999.[2] In contrast, US regions with the highest routine employment share have the largest per capita computer usage rate (Autor & Dorn, 2013, see Table 3).

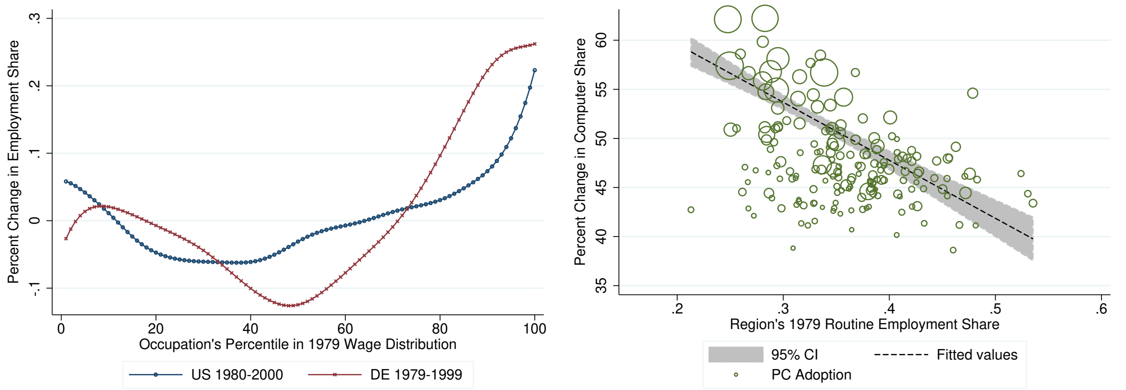
In this paper we argue that differences in educational systems can resolve this puzzle. Although Germany has an extensive apprenticeship system, there exists substantial variation in regional apprenticeship intensity. Figure 2a repeats Figure 1a for Germany across regions with above and below average new apprenticeship contracts from 1978/1979.[3] Regions with above average ratios in apprenticeship contracts (labeled "Apprentice Regions") have experienced significantly less employment polarization. Regions with little employment polarization are also regions with less computer adoption. Figure 2b sorts regions along the percentile distribution in terms of new apprenticeship contracts in 1978/79 and

[1] Autor et al. decompose occupation requirements into three task types: manual (hand and finger dexterity), routine (repetitive) and abstract (analytical). Generally, the low, middle and high portions of the income distribution are linked to manual, routine and abstract tasks, respectively.

[2] Details on the computer measure are provided in Section 3.3.

[3] New apprenticeship contracts are measured as the ratio of new contracts over the employed population within local labor markets.

Figure 1: **Employment Polarization and Computers**



(a) Employment Polarization

(b) Computer Adoption

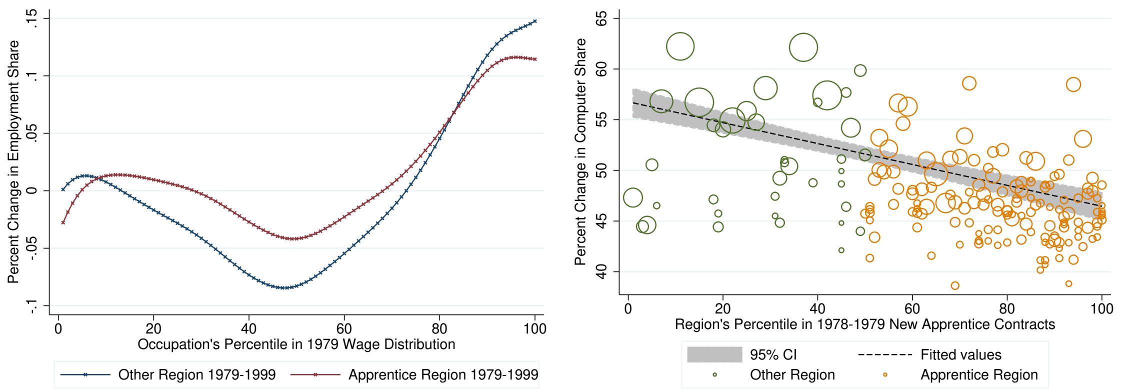
Note: US 1980/2000 census including all working individuals, that are not institutionalized, in school or in active-military duty (weighted by census weights multiplied by annual hours worked); German SIAB 1979/2000 samples and computer shares from QCS 1999 (for details see Appendix B).

graphs the per worker computer usage within each region by 1999. Regions with above average rates of new apprenticeship contracts in the 1978/1979 period have lower computer shares in 1999. The linear fit suggests a negative correlation of -0.45.

We develop a simple "skill-/task-replacing" model to demonstrate how non-college, routine task labor is prone to substitution by high-skilled workers using capital/machines. Building on the empirical fact that apprentice-skills are immobile, we extend the model to a spatial equilibrium setting where local labor markets have differential degrees of skill-specific workers (apprentices). From a firm's perspective, acquiring new machinery in areas where apprentices are employed is more costly because training (specific skill) becomes obsolete and the comparative advantage of the apprenticeship is lost.[4] The model predicts that regions using apprentices (i.e. non-college labor with specific human capital, instead of general workers): (1) adopt fewer computers; (2) face slower employment polarization or displacement of routine workers; and (3) exhibit a smaller rise in low-skilled services. We evaluate these hypotheses using German social security data across local commuter zones.

[4] The apprenticeship costs, estimated to be about €15,000 per year per apprentice by the *Bundesinstitut fuer Berufsbildung* (BiBB), are mostly born by firms (Harhoff & Kane, 1993; Soskice, 1994).

Figure 2: **German Regional Employment Polarization and Computer Adoption**



(a) Employment by Apprentice-Intensity (b) Computer Adoption by Apprentice-Intensity

Note: SIAB 1979/2000 samples, BiBB apprentice contracts 1978/1979, and QCS 1999 PC usage (for details see Appendix B).

The empirical results confirm the model's hypotheses. Regions with high apprenticeship rates have less computer adoption, less employment polarization and a smaller rise in service employment. The results for other (non-apprentice) routine-labor are similar in magnitude to the US from 1980 to 2000 in terms of labor displacement. Every additional 10 percentage points of routine-labor in 1979 result in a 2.19 percentage point displacement of routine-labor per decade. The results on computer adoption and service employment are in the same direction as in the US, but smaller in magnitudes. All results are robust to a number of specifications.

Germany with its dual education system provides a natural platform to study the differential impact of the computer revolution on employment of different skill-types. The (dual) apprenticeship system incentivizes firms to invest in industry- or firm-specific skills of its workforce. Winkelmann (1997) suggests that the institutional structure allowing the apprenticeship system to function in Germany is likely not present in the US. That is, greater labor mobility, flexibility in wages and reduced layoff costs in the US make it riskier for firms to train workers in case of "poaching" (Acemoglu & Pischke, 1998). Thus, High school graduates in the US are individuals that acquire general human capital at school, but receive very little specific training. In contrast, German apprentices acquire specific skills through training programs at firms.

If ICT capital replaces non-college workers (as suggested by Autor et al., 2003), firms in Germany have less incentives to adopt new technology and machines when compared to the US. Michaels et al. (2010) document the positive correlation between high-skill demand/high-skill wages and ICT adoption across countries. van Ark et al. (2003) show that the EU is "lagging" the US in terms of ICT capital adoption, and Germany is no exception, exhibiting a slow diffusion of ICT with no "catch up" effect.

Goldin & Katz (2008) hint that slower output growth in Europe could be a function of the vocational education emphasis. Krueger & Kumar (2004) formalize this argument and suggest that since the 1980s Europe has lagged behind in terms of manufacturing productivity and in total output growth due to vocational educational systems.

Our empirical approach is similar to Autor & Dorn (2013) who find that computer adoption has led to employment polarization and growth in low-skilled services for the US. We follow Autor & Dorn in using a spatial equilibrium concept (or commuting zones) to exploit cross-regional variation. Goos et al. (2011) study employment polarization resulting from technological change, offshoring and institutional differences across Europe. Findings across Europe also suggest that routinization has also played the largest part in employment polarization. Senftleben & Wielandt (2012) replicated the study of Autor & Dorn (2013) for Germany, finding employment, but no wage polarization.

To our knowledge, we are the first to link the educational system with a notion of both skill biased technical change (SBTC) and task biased technical change (TBTC), and employment polarization (see Acemoglu & Autor, 2011, for a detailed survey on SBTC and TBTC). Thus, we contribute to the literature on (1) SBTC versus TBTC by providing quantitative estimates of both effects, and (2) skill-specific versus general education by showing that a skill-specific education system is more immune to job polarization than a general education system. Our results further establish that the lack of polarization is likely a direct consequence of a skill-specific workforce reducing the economic incentive to adopted skill-replacing technology. We do not consider the findings unique to Germany, since results on non-apprentice labor are qualitatively and quantitatively similar to the US results by Autor & Dorn (2013). In contrast, regional variation within Germany allows for a natural experiment of general versus specific education without encountering a myriad of other potentially important cultural and institutional differences seen in cross-country variation.

The remainder of the paper is organized as follows: Section 2 presents the theoretical model and derives the testable implications. Section 3 provides a description of the data. Section 4 presents the empirical results and compares them both across regions within Germany and with the US. Section 5 concludes.

2 The Model

To model the interaction between apprenticeships and technological change, we develop a partial equilibrium model. Skill supplies are given, and the population is divided into non-college (apprentice or general education) and college graduates.[5] For brevity, we refer to non-college workers as "low-skilled" and college graduates as "high-skilled." These labels do not imply that the low-skilled acquire no skills, but the skill set is lower in terms of formal schooling.

2.1 The Environment

The model is loosely based on Acemoglu & Autor (2011) and Acemoglu & Zilibotti (2001), in which intermediate goods (tasks) are produced by differentiated labor or capital. Combing the two models allows for both the effect of SBTC and TBTC. The new key feature here is the addition of apprentices. Apprentices differ form other low skilled labor in having a larger productivity for certain tasks.

More specifically, the unique final good is made up of a continuum of intermediate

[5]For simplicity skill supplies are assumed fixed. Incorporating an endogenous education decision does not change the qualitative results of employment polarization.

goods sorted on the interval i from $[0, 1]$,

$$Y_t = \exp\left[\int_0^1 \ln y_t(i) di\right].$$

Each intermediate good has manual-, routine- and abstract-task components. Suppose goods are sorted on the interval $i \in [0, 1]$ from mostly manual to abstract task requirements, with routine task-intensity in the middle. Then, consistent with the TBTC literature, (1) the manual-intensive component is decreasing over the unit interval, (2) the routine-intensive component is an inverted U-shape on the interval of intermediate goods, and (3) the abstract component is increasing over the unit interval. Going forward, we refer to three distinct intervals, (1) $i \in [0, \underline{x})$ the low-skilled service interval, LST; (2) $i = [\underline{x}, \overline{x}]$ the routine interval, RT; and (3) $i = (\overline{x}, 1]$ the abstract interval, AT. Each intermediate good on the unit interval can be produced using machines and labor,

$$y_t(i) = \max\{\alpha_\ell(i), \mathbb{1}_{(\ell=a|i\geq\underline{x})}\hat{\alpha}_\ell(i)\}\ell_t(i) + (\alpha_h(i)h_t(i))^\beta \left[\int_0^{N_t} (\alpha_k(i))^\beta (k_t(i,v))^{1-\beta}\, dv\right],$$

where N_t captures the level of technology, which is exogenously given (e.g. adopted from the world technological frontier), $k_t(i, v)$ are machines in sector i of vintage v, and $\alpha_j(i) > 0$ captures the skill-specific comparative advantage of labor type j in producing good i. Firms choose how many machines to purchase and which type of worker to use for each task. Machines are produced by monopolists each period. Details of the production of machines are not essential for the results on polarization and can be found in Appendix A.

We make two assumptions regarding labor and capital productivity over the unit interval.

Assumption 1.

$\hat{\alpha}_\ell(i) > \alpha_\ell(i) \forall\, i \in [\underline{x}, 1]$.

Apprentices have relative higher labor productivity, $\hat{\alpha}_\ell(i)$ for tasks above $\underline{x}$, otherwise apprentices have the same labor productivity as other low-skilled worker. That is, low-skill production (e.g. sweeping), do not benefit from apprenticeship training.[6]

[6] The relative wage differential between apprentices and non-apprentices in the data suggests apprentices' comparative advantage to be largest in middle-wage jobs.

Assumption 2.

$\frac{\alpha_\ell(i)}{\alpha_h(i)}$ and $\frac{\hat{\alpha}_\ell(i)}{\alpha_h(i)}$ are continuously differentiable and strictly decreasing in i, with $\frac{\partial^2 \alpha_\ell(i)}{\partial i^2}, \frac{\partial^2 \hat{\alpha}_\ell(i)}{\partial i^2} < 0 \, \forall i$ and $\frac{\partial \alpha_k(i)}{\partial i} \leq 0 \, \forall i \, [\underline{x}, 1]$ and $\alpha_k(i) = 0 \, \forall i \, [0, \underline{x})$.

High-skilled labor is more productive in abstract tasks and the more abstract a production process is, the more difficult it is for low-skilled labor to be productive. As in the TBTC literature, goods production in the middle of the interval, which has a large routine component, can most easily be switched from production by labor to machines.

In the following sections, for simplicity of derivations, we assume that $\alpha_h(i) = \alpha_h$, the high-skilled productivity is constant across all goods, and $\alpha_k(i) \in \{\alpha_{k1}, \alpha_{k2}\}$ takes two distinct values with higher productivity in RT.[7] That is, the second part of Assumption 2 simplifies to, $\alpha_k(i) = \alpha_{k1} \equiv 1 \, \forall i \, [\underline{x}, \overline{x}]$ and $\alpha_k(i) = \alpha_{k2} < 1 \, \forall i \, (\overline{x}, 1]$.

To highlight differences in economies with and without apprentices we first define the equilibrium without apprentices and then develop a spatial equilibrium concept contrasting technological change in economies with and without apprentice-labor. Only main results are provided, necessary details of equations and derivations can be found in Appendix A.

2.2 Equilibrium without Apprentices

As in Acemoglu & Autor (2011) and Acemoglu & Zilibotti (2001), given Assumption 2, there is perfect sorting. Lemma 1 summarizes the production structure.

Lemma 1. *For any equilibrium, there is a threshold, J_t, such that for any $i < J_t, h_t(i)$, $k_t(i, v) = 0$, and for any $i \geq J_t$, $\ell_t(i) = 0$.*

To study the effect of technology displacing low-skilled labor from the routine interval, Assumption 3 guarantees that the economy's starting point is within the RT region.

Assumption 3.

The threshold on labor is within the RT regions for all time-periods, $J_t \in [\underline{x}, \overline{x}] \, \forall t$.

[7]Neither of these two simplifications on labor and capital change the qualitative results, but they simplify the derived equilibrium equations.

The demand of labor and capital is determined by profit maximization of final goods producers. In equilibrium the low- and high-skilled are equally distributed across goods,

$$\ell_t(i) = \frac{L}{J_t} \text{ and } h_t(i) = \frac{H}{1-J_t}. \tag{1}$$

We define, labor of low-skilled workers performing routine jobs, $i = [\underline{x}, J_t]$, as $L_{RT,t} := \frac{L}{J_t}(J_t - \underline{x})$, and, labor in low-skilled services, $i = [0, \underline{x})$, as $L_{LST,t} := L - L_{RT,t}$. Total machine demand, X_t, is given by,

$$X_t = \alpha_h N_t \frac{H}{1-J_t}\left[(\overline{x} - J_t) + (1-\overline{x})\,\alpha_{k2}\right]. \tag{2}$$

Given demand for machines and labor, there is a "no arbitrage" condition, which pins down the sorting threshold,

$$\frac{\alpha_h \alpha_k(J_t) H N_t}{1-J_t} = \frac{\alpha_\ell(J_t) L}{J_t}. \tag{3}$$

Technological Change

Totally differentiating the logarithm of Equation (3) with respect to $\ln(N_t)$, shows the effect of technological change on the sorting threshold,

$$\frac{dJ_t}{d\ln(N_t)} = \left(\frac{1}{\alpha_\ell(J_t)}\frac{\partial \alpha_\ell(J_t)}{\partial J_t} - \frac{1}{1-J_t} - \frac{1}{J_t}\right)^{-1} < 0. \tag{4}$$

Under Assumption 2 an increase in technology leads to a drop in the threshold. The range of goods produced by high-skilled workers increases at the expense of low-skilled workers. The demand for machines increases through (1) a direct effect $\frac{\partial ln(X_t)}{\partial ln(N_t)} = 1$, and (2) under Assumption 3, an indirect effect that occurs through a fall in the threshold J_t,

$$\frac{\partial \ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)} = -\frac{dJ_t}{d\ln(N_t)}\left(\frac{1}{\overline{x} - J_t} - \frac{1}{1-J_t}\right) > 0. \tag{5}$$

The low-skilled labor allocation is only affected through the indirect fall of the threshold,

$$\frac{\partial \ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)} = \left(\frac{\underline{x}}{(J_t - \underline{x})J_t}\right)\frac{dJ_t}{d\ln(N_t)} < 0. \tag{6}$$

As the relative fall in the number of routine-labor is always larger than the increase in the number of workers per good i, labor shifts to the production of low-skilled goods, $i < \underline{x}$, $\frac{\partial \ln(L_{LST,t})}{\partial J_t}\frac{dJ_t}{d\ln(N_t)} > 0$.

With the threshold pinned down, (relative) wages across skill groups can be derived. The labor market is competitive, hence workers are paid their marginal product. The skill premium is,

$$\frac{w_{ht}}{w_{\ell t}} = \frac{N_t \alpha_h \alpha_k(J_t)}{\alpha_\ell(J_t)}. \tag{7}$$

Equation (7) highlights that the skill premium is increasing in technology N_t, the complementarity effect. However, with fixed labor supplies, under Assumption 3, a fall in the threshold, J_t, compresses the skill premium as $\alpha_\ell(J_t)$ is decreasing in J_t and $\alpha_k(J_t) = 1$.

2.3 Spatial Equilibrium with Technical Change

To discuss differences across apprentice-intensive and general-education regions, we introduce an integrated spatial equilibrium model without labor mobility.[8] It is assumed that goods from all regions are perfect substitutes, ensuring equal regional prices in equilibrium.

For simplicity, the model analyzes two regions, where either all low-skilled are apprentices or none are apprentices. Therefore, the only difference between regions is the relative productivity of the low-skilled over RT, $\hat{\alpha}_\ell(i) > \alpha_\ell(i)$. We denote the "specific apprentice productivity" as λ, where $\hat{\alpha}_\ell = f(\alpha_\ell, \lambda)$ and $\frac{\partial \hat{\alpha}_\ell}{\partial \lambda} > 0$. *Ceteris paribus*, a region with apprentices has a higher threshold J_t,

$$\frac{dJ_t}{d\lambda} = -\frac{1}{\hat{\alpha}_\ell(J_t)} \frac{\partial \hat{\alpha}_\ell(J_t)}{\partial \lambda} \frac{dJ_t}{d\ln(N_t)} > 0. \tag{8}$$

More specifically, the apprentice productivity, $f(\alpha_\ell, \lambda)$, can take any functional form as long as it satisfies Assumptions 1 - 3, and

Condition 1.

$$\frac{d\frac{dJ_t}{d\ln(N_t)}}{d\lambda} > 0.$$

[8] Dustmann & Pereira (2008) show that job mobility (wage growth and returns to experience) is substantially lower in Germany compared to the UK. Adda et al. (2006) further document that apprentices, in particular, are less mobile and overall job mobility is substantially lower in Germany compared to the US. Since job mobility is a prerequisite for regional mobility, these facts also suggest low overall mobility.

Regions with apprentices have a slower fall in the threshold upon technology adoption. Condition 1 is satisfied under fairly weak restrictions (see Appendix A). For example, one productivity schedule that fulfills this condition is $\hat{\alpha}_\ell(i) = \alpha_\ell(i) \cdot \lambda(i)$ with $\frac{\partial \lambda(i)}{\partial i} < 0$.

Technological Change

The cross derivatives of Equations (5) and (6) with respect to the apprentice productivity, λ, summarize the technology effect between apprentice- and other regions. The differential effect of technology on the dependent variable, $Z_t \in \{\ln(X_t); \ln(L_{RT,t})\}$, is,

$$\frac{d\left(\frac{\partial Z_t}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{d\lambda} = \frac{\partial\left(\frac{\partial Z_t}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t}\frac{dJ_t}{d\lambda} + \frac{\partial\left(\frac{\partial Z_t}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial \lambda} < 0. \tag{9}$$

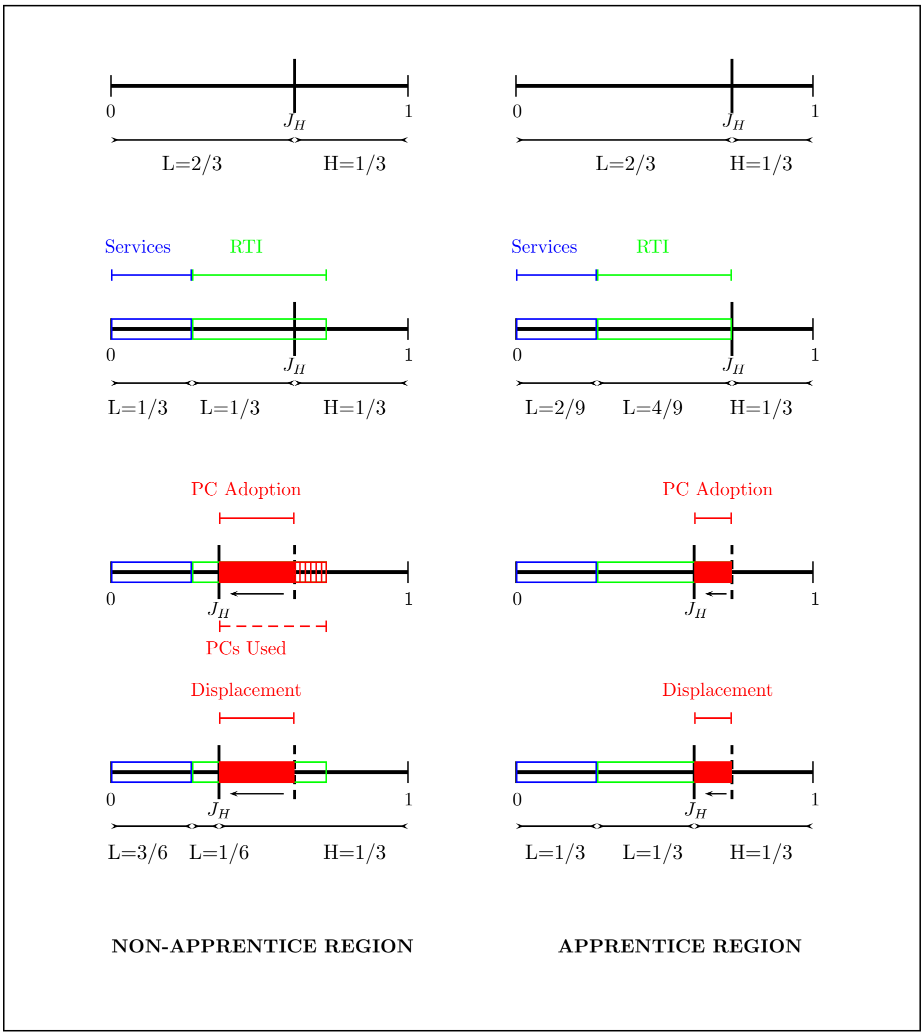
Under Assumptions 1 - 3 and Condition 1, it can be shown that apprentice-regions have less machine adoption, X_t and less routine-labor displacement, $L_{RT,t}$ (or less growth in low-service employment, $L_{LST,t}$).

Proof. See Appendix A. □

These results follow from the negative threshold growth accelerating as the threshold decreases, $\frac{d^2 J_t}{d\ln(N_t)dJ_t} > 0$, and this occurring more slowly for apprentice regions $\frac{\partial \frac{d^2 J_t}{d\ln(N_t)dJ_t}}{\partial \lambda} < 0$. Intuitively, adding one additional good to the set of goods $1 - J_t$, is relatively less costly, the more goods are already produced by the high-skilled with machines. In addition, apprentice regions have higher initial thresholds.

Figure 3 visualizes the effect of machine adoption and routine-labor displacement. The complementarity effect, conditional on regions having the same high-skilled labor share, is identical in apprentice- and other regions. The differential speed of machine adoption across regions is only driven by differences in the substitution channel (of the low-skilled). Intuitively, apprentices are more productive than other low-skilled workers and, therefore, the opportunity cost of replacing them is larger - the threshold is initially higher and it falls at a slower rate for any given replacement (machine) cost. Consequently, at any given technology level, fewer machines are adopted and less labor is displaced from routine employment into the low-skilled service sector. In terms of wages, the skill premium

Figure 3: **Hypotheses 1 and 2**



Note: The figure displays the change in the occupational structure across regions facing an increase in ICT capital. This effect is displayed for a non-apprentice region in the left panel and for an apprentice-intensive region in the right panel.

in apprentice regions is smaller than in other regions for any given threshold, J_t, and apprentices earn a premium when working as apprentice labor (utilizing their skills),

$$\frac{w_{ht}}{w_{\ell_x t}} = \frac{N_t \alpha_h \alpha_k(J_t)}{\hat{\alpha}_\ell(J_t)} \quad \text{and} \quad \frac{w_{\ell_x t}}{w_{\ell_{x_{-1}} t}} = \frac{\hat{\alpha}_\ell(J_t)}{\alpha_\ell(\underline{x})} \quad if\ J_t \geq \underline{x}. \tag{10}$$

Given the results on speed of technology adoption above, the college premium increases at a slower rate in apprentice regions. As the threshold falls, J_t approaches $\underline{x}$, the apprentice premium disappears and Equation (10) converges to Equation (7). Therefore, the loss of the apprentice premium can be viewed as wage polarization to the left and right tails of the distribution.

2.4 Testable Implications and Empirical Specification

Using the results from Equation (9), we derive three testable implications across commuting zones for the dependent variable, $Z_t \in \{\ln(X_t); \ln(L_{RT,t}); \ln(L_{LST,t})\}$.

Empirical Specification

The change in the threshold parameter (J_t) only changes with exogenous technological progress over time. Therefore, the effects of technology on the dependent variable (Z_t) is,

$$\frac{\partial Z_t}{\partial J_t} \frac{dJ_t}{d\ln(N_t)} \approx \frac{\Delta Z_t}{\Delta J_t} \frac{\Delta J_t}{\Delta t}.$$

Without apprentices, the change in J_t over time only depends on the region's *initial* J_0. However, thresholds are an abstract concept and not observed in the data. In contrast, a region's routine-labor share is observable, $\ell_{RT,0}$. Without apprentices, since all regions face the same global technology frontier, the initial routine-labor share, $\ell_{RT,0}$, captures all the variation in the threshold J_0. Ergo, the threshold is identified by the routine-labor share, $\ell_{RT,0}$,

$$\frac{\Delta Z_t}{\Delta J_t} \frac{\Delta J_t}{\Delta t} \equiv \Delta(Z_t - Z_0)\Big|_{J_0} \approx \Delta(Z_t - Z_0)\Big|_{\ell_{RT,0}}.$$

Using the initial routine-labor share as identification, the baseline regressions corresponding to Equations (5) and (6) are,

$$\Delta Z_{t,j} = \beta_0 + \beta_1 \ell_{RT,0,j} + \epsilon_j. \tag{11}$$

When differentiating between apprentices and other low-skilled labor, the routine-labor share, $\ell_{RT,0}$ does not uniquely define the threshold, J_0. A region's threshold is determined by (1) the share of high-skilled labor and (2) the composition of low-skilled labor (apprentices or others). Only conditional on the high-skilled labor share does a region with more apprentices have a higher threshold given technology. Equation (9), can be rewritten as,

$$\frac{d\left(\frac{\partial \Delta Z_t}{\partial J_t} \frac{dJ_t}{d\ln(N_t)}\right)}{d\lambda} = \frac{d\Delta(Z_t - Z_0)}{d\lambda}\Big|_{\ell_{RT,0},h_0}.$$

The regression showing the differential effect of apprentice and other low-skilled labor across regions is,

$$\Delta Z_{t,j} = \beta_0 + \beta_1 \ell^A_{RT,0,j} + \gamma_1 \ell^O_{RT,0,j} + h_{0,j} + \epsilon_j. \qquad (12)$$

The superscript, A, stands for apprentice labor and, O, for other low-skilled labor, with $h_{0,j}$ being a region's initial high-skilled share.[9]

Testable Implications

The resulting testable implications of Equation (9) are:

Hypothesis 1. *Conditional on the high-skilled labor share, regions with an apprentice-intensive industry structure adopted fewer computers (X_t) over time.*

Hypothesis 2. *Apprentice-intensive regions, conditional on the high-skilled labor share, have less displacement of routine-labor ($L_{RT,t}$) as ICT technology progresses.*

Hypothesis 3. *Apprentice-rich regions experience a smaller rise in low-skilled services ($L_{LST,t}$) over time, conditional on the high-skilled labor share.*

3 German Regional Data

This section summarizes the construction of key variables and data sources. Further detail is provided in Appendix B.

3.1 Data Sources

Two main data sources are used in this paper: (1) the Sample of Integrated Labor Market Biographies - Regional File 1975-2008 (SIAB); and (2) the BIBB/IAB Qualification and Career Survey 1979 and 1999 (QCS). The SIAB sample provides detailed individual-level characteristics, such as education, region of work, nationality, and labor market experience

[9] Unlike the theory, regions do not perfectly sort into apprentice versus non-apprentice regions, as regions have different mixes of the two types of educational systems. Therefore, it is necessary to differentiate between apprentice and other low-skilled labor.

(e.g. occupational status and wages) (see Dorner et al., 2011, for details). The sample used consists of all workers subject to social security payments, aged 17 to 62. The QCS is used to construct occupation-specific computer usage.

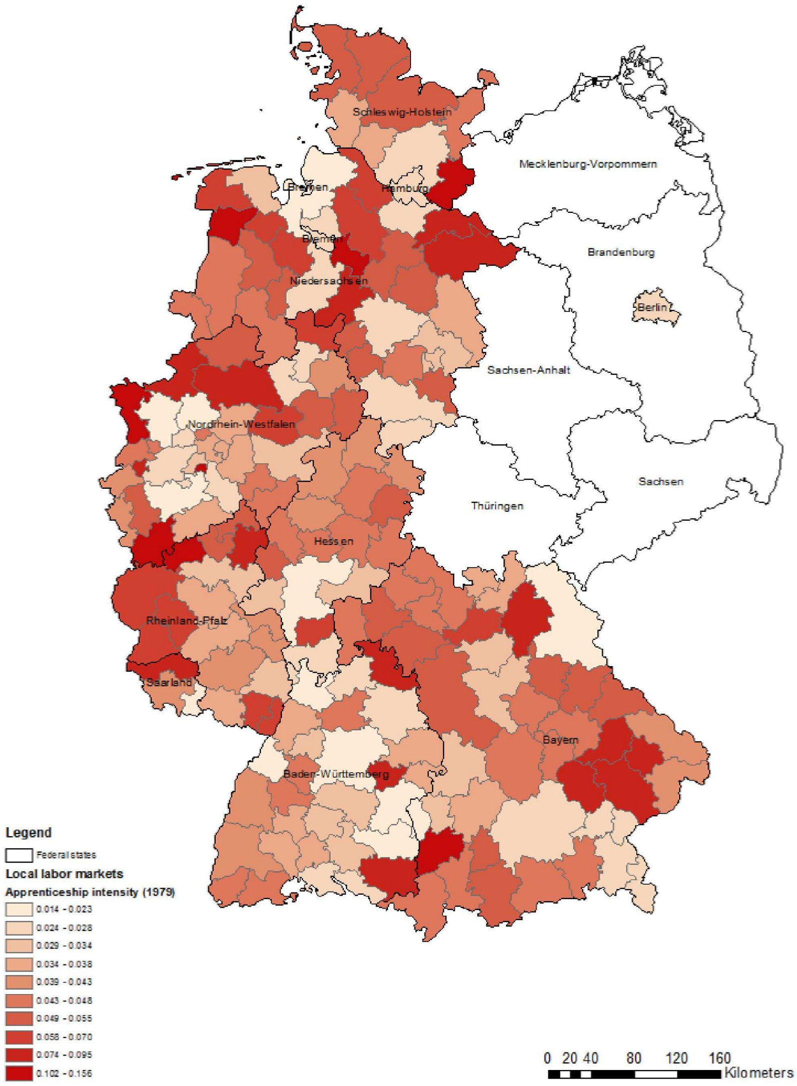
Given the fragmented apprenticeship system prior to the late 1970s, Germany provides an ideal natural experiment to test the hypotheses on computer adoption and employment polarization across general versus specific education systems. More specifically, before the ratification of the *Berufsbildungsgesetz* at the beginning of the 1970s and the introduction of the *Ausbildungsplatzfoerderungsgesetz* in 1976, the apprenticeship system was regionally fragmented with states individually deciding how to support the apprenticeship system. Only after the two oil shocks and the following deterioration of employment opportunities for young adults did the federal government provide a systematic federal structure (or incentives) to educate the workforce.[10] To compute regional variation we use the official definition of local labor markets (or commuting zones) from the "Bundesinstitut fuer Bau-, Stadt- und Raumforschung," (for details see Koller & Schwengler, 2000). These zones are based on economic geography, accounting for commuter flows and commuting time (Eckey, 1988; Eckey & Klemmer, 1991). Using the SIAB dataset for West Germany results in 182 commuting zones across 11 states. Figure 4, sorting local labor markets into deciles of new apprenticeship contracts in 1978/1979, shows the initial regional variation. There is no clear North-South or East-West pattern in the late 1970s. Thus, our empirical analysis uses initial regional variation in apprentice- and routine employment shares to determine the interaction between education, ICT adoption and labor market polarization while controlling for state fixed effects.

3.2 Apprentices

Apprenticeship rates in Germany are high and stable over time. The BiBB (1977, 2011) documents 496,000 new apprenticeship contracts in 1976 (67 percent of all secondary graduates) and 468,410 new contracts in 2010 (65 percent of secondary graduates). While initial

[10]See Casey (1991), BiBB (1977); Soskice (1994) and references therein for a detailed discussion of the apprenticeship system history in Germany.

Figure 4: **Germany Apprenticeship Intensity in 1979**



Note: BiBB apprentice contracts 1978/1979.

apprenticeship numbers are large, a considerable fraction eventually switch industries and occupations, making most of the specific knowledge obsolete. BiBB (1977) reports that about 40 percent of male apprentices between 1955 and 1970 switched their broad sector of work. About half of them document that their specific skills became obsolete (see also Adda et al., 2006). In the QCS sample, about 50 percent of apprentices switch industry and about 31 percent switch the broad sector (services to non-services). In the empirical analysis, we label workers as apprentices if they completed an apprenticeship in the same broad sector they are currently employed in.

3.3 Computer Adoption Measure

The computer measure is tabulated from the 1999 QCS. Survey takers are asked whether they use personal computers (PCs) during their regular work. We construct an occupation k specific PC measure as the average share of workers within each occupation that use a PC. Since PC usage varies between different sectors, we differentiate between the broad sector of services and non-services (sector is denoted by s, occupation by k, individual by i).

$$PC_{sk}^{99} = \left(\sum_{s=1}^{S} \sum_{i=1}^{I} L_{isk,1999} \cdot 1 \left[PCuse_{isk,1999} = YES \right] \right) \left(\sum_{s=1}^{S} \sum_{i=1}^{I} L_{isk,1999} \right)^{-1} .$$

We adopt the standard procedure of assuming that the share of computers in 1999 also captures the growth in computer utilization since 1979, i.e., computers were virtually absent in 1979. The QCS allows us to compute computer adoption by occupations, and the SIAB provides the regional variation in occupational structure. That is, it is assumed that a given occupation adopts computers in a similar way, regardless of geographical location. Using the SIAB panel data and regional employment shares of each occupation in 1999 as weights, a weighted mean of PC usage within a region j is,

$$PC_{j}^{99} = \left(\sum_{s=1}^{S} \sum_{k=1}^{K} L_{jsk,1999} \cdot PC_{sk}^{99} \right) \left(\sum_{s=1}^{S} \sum_{k=1}^{K} L_{jsk,1999} \right)^{-1} .$$

3.4 Measuring Inputs

Since the data is available on an individual level, we measure inputs to the production process on an occupational level rather than the intermediate goods level as in the model. However, only the aggregate regional input levels matter in our analysis and not how they are distributed across individual occupations.

Figure 5: **Share of RTI Occupations (DOT vs BiBB) in 1979**

Note: German SIAB 1979/2000 samples, US DOT 1977 and QCS 1979. For details see Appendix B.

We use task measures computed by Autor & Dorn (2013) for the US from the Dictionary of Occupational Title (DOT) to compute task-intensity across the German working population. We do so in order to make the results comparable to other studies. The empirical analysis uses both separate tasks as well as the compounded routine measure,

$$R_j = \frac{Routine_j}{Routine_j + Manual_j + Abstract_j},$$

for occupation j. Routine tasks are an average of routine-cognitive and routine-manual tasks. Abstract tasks are the average of non-routine personal and non-routine analytical. Manual tasks are the non-routine manual tasks (for further details see Autor et al., 2003). As in Autor & Dorn, an occupation is labeled routine-task-intensive, RTI_j, if the occupation falls within the top one-third of the employment distribution in terms of the R_j measure,

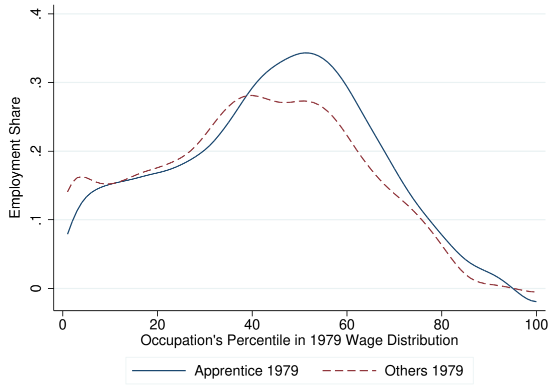
$$RTI_j = \mathbf{1}\left[R_j \geq R^{P66}\right]. \tag{13}$$

For the analysis of machine adoption we also compute the 66th percentile index for the separate task measures (manual, routine and abstract).

Applying US task measures to German occupations could potentially be problematic. While the QCS also identifies routine, manual, and abstract tasks, questions are not identical to the US survey and, therefore, will not necessarily capture the same information.

Figure 6: **Share of Routine Occupations (Apprentices vs Others) in 1979**

(a) RTI



(b) Routine

Note: German SIAB 1979/2000 samples and US DOT 1977. For details see Appendix B.

However, a comparison between German and US task measures, applied to the SIAB sample, shows similar aggregate results. More specifically, Figure 5 shows the share of employment within RTI-occupations for both the DOT and the QCS measures across the 1980's wage distribution. Most of the employment in RTI-occupations occurs in the middle of the wage distribution (for the US equivalent, see Figure 4 in Autor & Dorn, 2013).

It is also important to establish that both apprentices and non-apprentices could potentially be replaced by ICT technology. If apprentices were to perform very different tasks (i.e. tasks that are not routine in nature), it would not be surprising that apprentices are not displaced by ICT. Figure 2 would be the product of apprentices being irreplaceable and not acquired skills increasing their relative productivity. Figure 6 graphs the share of routine employment from Figure 5 separately by apprentices versus other workers. The left panel (Figure 6a) graphs the aggregate RTI measure in employment shares and the right panel (Figure 6b) graphs the 66th percentile employment share of occupation that are *Routine* (individual task measure). Although apprentices perform less RTI tasks along the lower part of the wage distribution, the overall employment in RTI tasks is similar to other workers. Comparing only the routine component suggests that apprentices and other workers engage in virtually the same amount of routine-employment, especially in the middle of the wage distribution, where the majority of employment polarization has taken place. The difference in the aggregate RTI measures is driven by some apprentice occupations performing more manual tasks than other workers.

4 Empirical Results

We separately test our three hypotheses from Section 2.4 on: (1) computer adoption, (2) routine-labor displacement, and (3) and service sector growth.

To do this formally, cross-section OLS regressions are estimated with and without state fixed effects (ψ_f) and year fixed effects (θ_t) when appropriate. Standard errors use the cluster-robust estimate of the variance matrix (CRVE) unless otherwise noted. Following Cameron & Miller (2015) we also report wild cluster bootstrap p-values testing for the wil hypothesis of each coefficient equalling zero. Regressions are weighted by each periods' initial regional employment shares and all variables are constructed on a regional labor market level. For example, the regional measure of routine-task-intensity, RTI, is defined as the share of employment within region j that works in RTI-occupations k,

$$RTI_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot RTI_k \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1} .$$

As the data only has computer shares and employment shares across regions (with some equalling zero), rather than estimating regressions in log-scale, Z_t, the empirical counterpart uses shares, $Z_t \in \{x_t; \ell_{RT,t}; \ell_{LST,t}\}$.

4.1 Computer Adoption and Skills

Hypothesis 1. *Conditional on the high-skilled labor share, regions with an apprentice-intensive industry structure adopted fewer computers (X_t) over time.*

To determine the validity of Hypothesis 1, we test whether the adoption of personal computers can be explained by the share of RTI-occupations and/or the share of abstract-occupations in a region. The former suggests ICT is substitutable with the low-skilled (or routine tasks) and the later suggests ICT is complementary with the high-skilled (or abstract tasks).

Without differentiating between apprentices and others, we regress the share of computers in 1999, $PC_{j,99}$, on the regional measure of routine-task-intensity, $RTI_{j,79}$,[11]

$$PC_{j,99} = \beta_0 + \beta_1 RTI_{j,79} + \psi_f + \epsilon_j.$$

The coefficient on $RTI_{j,79}$, consistent with the general employment polarization hypothesis, should be positive, $\beta_1 > 0$. Alternatively, the correlation of adoption and labor requirements can be decomposed by separate tasks,

$$PC_{j,99} = \beta_0 + \beta_1 Routine_{j,79} + \beta_2 Abstract_{j,79} + \beta_3 Manual_{j,79} + \psi_f + \epsilon_j.$$

By definition, the share of manual-, routine-, and abstract employment within a region do not necessarily sum to one. Occupations are only classified as either manual, routine or abstract if they meet the 66th percentile employment share threshold from Equation (13). The coefficient on routine-labor should be positive, $\beta_1 > 0$. In addition, the coefficient on abstract-labor should also be positive, $\beta_2 > 0$ and if the complementarity effect is stronger than the substitution effect, the latter coefficient should be greater, $\beta_2 > \beta_1$. Since manual-labor is neither a complement nor substitute to computers, the coefficient should be zero, $\beta_3 = 0$.

Table 1 summarizes the results, where columns (1) - (2) use the compounded RTI measure, columns (3) - (4) use the individual *Routine* measure, and columns (5) - (6) use the three separate measures to distinguish between substitution and complementarity effects. Each regression is first computed without and then with state fixed effects. Columns (1) - (4) suggest, counter to the general polarization theory, that more routine employment is associated with less computer adoption. In contrast, the results of columns (5) and (6), when including all task measures separately, suggest that both the substitution-of-routine-skills and complementary-to-abstract-skills are present in Germany, but the substitution effect

[11] Although the 1979 QCS does provide computer utilization information, we do not rely on this data since the survey design changed substantially since 1979. Defining computer adoption in 1999 as the change between computer utilization in 1999-1979 provides similar results (see Appendix O, Tables O.1 and O.2).

Table 1: **PC Adoption and Tasks**

	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. Variable: PC share in 1999					
RTI	-0.591***	-0.660***				
	(0.113)	(0.106)				
Routine			-0.602***	-0.663***	0.223**	0.143**
			(0.082)	(0.070)	(0.094)	(0.044)
Abstract					1.137***	1.133***
					(0.089)	(0.039)
Manual					-0.074	0.018
					(0.056)	(0.063)
State FE	No	Yes	No	Yes	No	Yes
Wild p-value						
RTI/Routine	*.011*	*.006*	*.005*	*.006*	*.061*	*.014*
Abstract					*.003*	*.008*
N	182	182	182	182	182	182
R^2	0.402	0.530	0.523	0.632	0.767	0.818

Notes: Standard errors are clustered at the state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

is considerably smaller. Across regions, 10 percentage points more routine employment in 1979 leads to 1.4 percentage points more computer adoption, whereas 10 percentage points more abstract employment in 1979 results in a 11.3 percentage point greater computer share in 1999. There is no effect from the manual component. The wild cluster bootstrap p-values (mostly below 1 percent for each individual coefficient) suggest there is no small cluster bias.[12] Results in column (6) are in line with results reported by Senftleben & Wielandt (2012) even though this paper uses different task measures.

[12] All results are robust across a number of specifications, e.g., pair cluster bootstrap estimations. Results in future tables omit the reporting of wild cluster bootstrap p-values unless they alter the conclusion.

To test Hypothesis 1, we differentiate the share of workers in RTI-occupations into apprentice-intensive ($ARTI$) and other occupations ($ORTI$),

$$\begin{aligned} ARTI_{j,t} &= \left(\sum_{k=1}^{K} L_{j,kt} RTI_k \times APP_k\right)\left(\sum_{k=1}^{K} L_{j,kt}\right)^{-1}, \\ ORTI_{j,t} &= \left(\sum_{k=1}^{K} L_{j,kt} RTI_k \times (1 - APP_k)\right)\left(\sum_{k=1}^{K} L_{j,kt}\right)^{-1}, \\ &\Rightarrow \ ARTI_{j,t} + ORTI_{j,t} = RTI_{j,t}, \end{aligned}$$

where APP_k indicates if the job is apprentice-intensive and, thus, has an apprentice-share above the 66th percentile. Since Table 1 shows a larger complementarity than substitution effect, the next results use decomposed task measures. The computer (PC) measure in 1999, $PC_{j,99}$, is regressed on $Routine_{j,79}$, $Abstract_{j,79}$, and $Manual_{j,79}$ employment shares,

$$\begin{aligned} PC_{j,99} &= \beta_0 + \beta_1 ARoutine_{j,79} + \beta_2 AAbstract_{j,79} + \\ &\quad \gamma_1 ORoutine_{j,79} + \gamma_2 OAbstract_{j,79} + \delta Manual_{j,79} + \psi_f + \epsilon_j. \end{aligned} \tag{14}$$

Even though Equation (12) is conditional on the high-skilled share, the control is omitted, as the correlation between $Abstract$ and the high-skilled share is 0.926. Theoretically, the coefficient on routine-labor should be smaller in the apprentice region, $0 < \beta_1 < \gamma_1$, while the abstract component should have similar effects across the different regions, $\beta_2 = \gamma_2$.

In columns (1) and (2) of Table 2 the coefficients on abstract employment are smaller for apprentices than other workers, but the two measures are qualitatively comparable. The null hypothesis, $H_0 : \beta_2 = \gamma_2$, cannot be rejected at the five percent confidence level ($F(1, 8) = 3.49$ with fixed effects). Therefore, columns (3) and (4) repeat regression (14) with the $Abstract$-measure over all worker types. With fixed effects, the coefficient on apprentice routine-labor is near zero (and not statistically significant), while every additional 10 percentage points of $ORoutine$-labor leads to a 1.5 percentage point increase in our PC measure. Thus, the full substitution effect from Table 1 is driven by other workers, not apprentices. This is precisely the theoretical prediction from Section 2. Wild cluster bootstrap p-values on $ARoutine$- (above 0.5) and $ORoutine$-labor (below 0.05)

Table 2: **PC Adoption, Apprentices and Tasks**

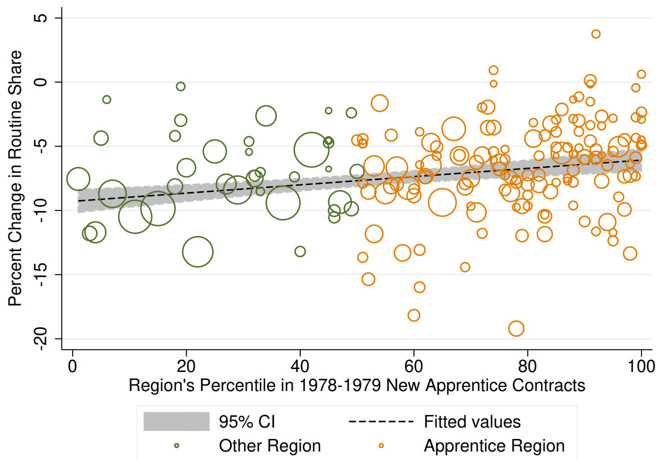
	(1)	(2)	(3)	(4)
	Dep. Variable: PC share in 1999			
ARoutine	0.104	0.004	0.143	0.016
	(0.243)	(0.240)	(0.254)	(0.242)
ORoutine	0.213*	0.153**	0.232**	0.154**
	(0.092)	(0.066)	(0.099)	(0.055)
AAbstract	0.826***	0.858***		
	(0.131)	(0.164)		
OAbstract	1.632***	1.585***		
	(0.256)	(0.275)		
Abstract			1.150***	1.150***
			(0.098)	(0.058)
Manual	-0.073	0.023	-0.055	0.046
	(0.059)	(0.069)	(0.084)	(0.100)
State FE	No	Yes	No	Yes
Wild p-value				
A Routine	*.655*	*.960*	*.586*	*.948*
O Routine	*.005*	*.008*	*.043*	*.008*
N	182	182	182	182
R^2	0.792	0.835	0.767	0.819

Notes: Standard errors are clustered at the state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

further corroborate the results.[13] The coefficient on manual employment is insignificant (the coefficients are also insignificant if estimated separately by apprentices and other workers).

[13] Wild cluster bootstrap p-values on abstract coefficients are similar to the CRVE p-values.

Figure 7: **Displacement by Region and 1979 Apprentice Intensity**



Note: German SIAB 1979/2000 samples and BiBB apprentice contracts 1978/1979.

4.2 Routine-Labor Displacement

Hypothesis 2. *Apprentice-intensive regions, conditional on the high-skilled labor share, have less displacement of routine-labor ($L_{RT,t}$) as ICT technology progresses.*

The model suggests that with less computer adoption, apprentice-intensive regions should experience less displacement of routine-labor. Visually, Figure 7 shows the correlation of apprentice-intensity and routine-labor displacement in a similar manner as Figure 2b for computers. The negative raw correlation between the share of new apprentice contracts in 1978/1979 and the displacement of RTI-labor shares for the 1979-2008 time period is -0.26.

Not accounting for apprentices, we regress the change in routine task intensity (the employment share in routine-intensive occupations) on the period's initial routine task intensity,

$$\Delta^{(t+10)-t} RTI_j = \beta_0 + \beta_1 RTI_{j,t} + \psi_f + \theta_t + \epsilon_j. \tag{15}$$

Given the theoretical framework and the evidence from the US, the coefficient on RTI-labor should be negative, $\beta_1 < 0$. Table 3 reports results for the compounded task measure only, although results for the separate routine measures are comparable. The results of regression (15) are reported in column (1) with standard errors clustered at the state level

Table 3: **Routine Displacement, Apprentices and Tasks**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dep. Variable: Δ RTI						
	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	Δ^{89-79}	Δ^{99-89}	Δ^{08-99}
RTI	-0.071	-0.071					
	(0.040)	(0.065)					
ARTI			0.010	0.010	-0.003	0.064	0.025
			(0.131)	(0.077)	(0.243)	(0.103)	(0.234)
ORTI			-0.219***	-0.219*	-0.079	-0.406**	-0.207*
			(0.052)	(0.114)	(0.050)	(0.123)	(0.092)
High-Skill			-0.271***	-0.271***	-0.285**	-0.442**	-0.245**
			(0.058)	(0.078)	(0.088)	(0.141)	(0.078)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes			
Cluster	State	2-way	State	2-way	State	State	State
N	546	546	546	546	182	182	182
R^2	0.309	0.309	0.371	0.371	0.152	0.490	0.163

Notes: Standard errors are clustered at the state level (and year - in 2-way cluster) and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

and in column (2) at both the state level and year (two-way cluster). The dependent variable is the decade change in the routine share. The coefficient in columns (1) and (2) are negative but insignificant.

Columns (3) and (4) of Table 3 repeat the exercise, but differentiating by apprentice and other employment. Following Equation (12), the change in employment is regressed on initial apprentice or other RTI-employment and the initial high-skilled labor share, $h_{t,j}$,

$$\Delta^{(t+10)-t}RTI_j = \beta_0 + \beta_1 ARTI_{j,t} + \gamma_1 ORTI_{j,t} + \delta h_{t,j} + \psi_f + \theta_t + \epsilon_j. \quad (16)$$

The coefficient on routine-labor should be negative and, in absolute value, smaller for apprentice employment, i.e. $\gamma_1 < \beta_1 \leq 0$. The results corroborate the theory, finding displacement of other workers, but not apprentices. Over a decade, an additional 10 percentage point in $ORTI$-labor results in a 2.19 percentage point displacement of RTI labor.[14] Similarly, Autor & Dorn (2013) find a 2.95 percentage point displacement per decade in the US (see Table 3 in that paper). In contrast, $ARTI$-labor has no displacement. These results are robust to a number of additional controls, e.g. the employment share in services, the female employment share, the share of immigrants, the share of youth (age 25 and below), and the share of part-time workers. With the additional controls, the coefficient on $ARTI$-labor is still insignificant. The coefficient on $ORTI$-labor varies between -0.395 and -0.215, and is significant at the one percent confidence level (see Tables O.3 and O.4 in Appendix O). Columns (5) - (7) show results separately for each decade,[15] highlighting the significant displacement during the 1990s, which aligns with the timing of mainstream ICT adoption (Nordhaus, 2007).

Table 4 shows the effect over a longer time horizon, from 1979 to 1999 and from 1979 to 2008. The change in routine employment shares between $t = 0$ and $t = T$ is regressed on the initial routine intensity in 1979. Aggregate effects are negative and wild cluster bootstrap p-values suggest the results are significant at five percent. Across regions, a 10 percentage point higher RTI-labor share in 1979 has a 0.9 percentage point lower RTI-labor share within 10 years, and a 1.8 percentage point decrease after 20 years. Over the entire 29 years, the result is slightly smaller. The results for columns (2) and (4) support differences between apprentices and other labor. There is no effect for $ARTI$-labor. For $ORTI$-labor the effect is similar in magnitude to the US.

4.3 Routine Shares and Service Employment

Hypothesis 3. *Apprentice-rich regions experience a smaller rise in low-skilled services ($L_{LST,t}$) over time, conditional on the high-skilled labor share.*

[14] Using the separate *Routine* measure gives a slightly smaller, but still comparable impact of 1.7 percentage points in a decade.

[15] To make results comparable across decades, column (7) is adjusted for the missing years. All results in Table 3 can be interpreted as 10-year changes.

Table 4: **Routine Displacement, Apprentices and Tasks in the Long-run**

	(1)	(2)	(3)	(4)
	Dep. Variable:Δ RTI			
	Δ^{99-79}	Δ^{99-79}	Δ^{08-79}	Δ^{08-79}
RTI	-0.182*		-0.124	
	(0.094)		(0.067)	
ARTI		0.036		0.023
		(0.214)		(0.210)
ORTI		-0.472**		-0.448***
		(0.146)		(0.047)
High-Skill		-0.870**		-1.019***
		(0.260)		(0.121)
State FE	Yes	Yes	Yes	Yes
Wild p-value				
A Routine		*.792*		*.890*
(O) Routine	*.032*	*.010*	*.043*	*.010*
N	182	182	182	182
R^2	0.318	0.484	0.342	0.535

Notes: Standard errors are clustered at the state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Does the displacement of routine-labor lead to a rise in low-skilled services? We follow Blossfeld (1985) in defining the low-skilled service sector. Low-skilled service occupations range from "hairdresser" and "street and indoor cleaners" to "attending on guests" and "nursing assistants."

Table 5 regresses the change in the low-skilled service sector share on the same set of variables as above. The results are presented in decades, similar to regressions (15) and (16). Given the cross derivative, Equation (9), the coefficients should have the opposite signs of the comparable coefficients in Tables 3 and 4. Column (1) suggests that routine-

Table 5: **Low-Skilled Services, Apprentices and Tasks**

	(1)	(2)	(3)	(4)	(5)
			Dep. Variable:Δ LS		
	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	Δ^{99-79}	Δ^{08-79}
RTI	0.023*				
	(0.014)				
ARTI		-0.014	-0.008	-0.074	-0.178
		(0.057)	(0.067)	(0.096)	(0.164)
ORTI		0.024	0.028	0.072***	0.111***
		(0.035)	(0.024)	(0.020)	(0.032)
High-Skill		-0.010			
		(0.035)			
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes		
Wild p-value					
A Routine		*.971*	*.985*	*.462*	*.450*
(O) Routine	*.045*	*.499*	*.191*	*.044*	*.102*
Cluster	2-way	2-way	2-way	State	State
N	546	546	546	182	182
R^2	0.499	0.499	0.499	0.209	0.214

Notes: Standard errors are clustered at the state (and year - in 2-way cluster) level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

labor and the growth in low-skilled services are positively correlated, with a magnitude approximately one-third of the US effect. This result is consistent with the smaller polarization on the left tail of Figure 1. Column (2) controls for the high-skilled labor share and splits the results by apprentices versus other routine-labor. Both results are insignificant when controlling for the high-skilled labor share. Not controlling for the high-skilled share (column (3)) lowers the wild cluster bootstrap p-value, but only marginally. This is consistent with Manning (2004) and Mazzolari & Ragusa (2013), who suggest that high-skilled labor demands low-skilled services. Columns (4) and (5) show long-run trends which are significant for $ORTI$-labor. The results are similar in magnitude to the entire time period. Having a 10 percentage point larger $ORTI$-labor share in 1979 leads to a growth in low-skilled services of 1.1 percentage points over the entire three-decade period, compared to a 1.1 percentage point increase over a single decade in the US (see Autor & Dorn, 2013, Table 5).

4.4 Wage Polarisation

Although the model has implications for wages, the study of wages is beyond the scope of this paper due to country specific issues. While Germany has seen no wage polarization, it has experienced wage dispersion (due to employment polarization). Consistent with the complementarity of ICT technologies and high-skilled labor, the top of the skill distribution has had the highest wage growth. Dustmann et al. (2009) find a rise in the wage differential of middle-skilled (apprenticeship holders) relative to the low-skilled starting in the 1980s. However, they find no clear trend between the high- and middle-skilled. The conclusion of the literature is that wage adjustments have been avoided due to institutional policies, e.g., centralized wage bargaining and generous unemployment benefits (see Dustmann et al., 2009; Kohn, 2006; Antonczyk et al., 2010; Senftleben & Wielandt, 2012). Given the limited evidence in the SIAB data sample, and that an analysis of wage polarization would need to account for different regional-specific institutional factors, it is outside the scope of this study to further investigate these trends.

5 Conclusion

ICT technology adoption has led to substantial employment polarization across the world. The standard theory suggests that routine tasks performed by the middle-skilled are most prone to displacement by computers. However, when quantifying the investment in computer adoption over the last decades across German regions, the data suggests that regions with the least routine employment have the most computer adoption. This apparent puzzle - which stands in sharp contrast to the US - is resolved by studying the composition of non-college labor in Germany.

The stylized model demonstrates the importance of the educational-system, i.e., general versus specific training, in incentivizing firms to adopt skill-replacing technologies. Since firms that train apprentices invest resources in doing so, the adoption of ICT technologies that replace non-college labor is more costly. As apprentices are more productive than other middle-skilled labor, due to their specific training, regions with a large number of apprentices see less ICT adoption, but also less displacement of routine-labor.

For the empirical analysis, we utilize "random" regional variation in apprentice-intensity across local German labor markets prior to the 1980s. The empirical results show virtually no displacement of apprentice-routine-labor. In terms of routine-labor displacement of other (non-apprentice) workers, the effects are similar to the US. An exception are the results on service employment, which are qualitatively the same as in the US, but significantly smaller. Lastly, most of the ICT adoption in Germany is driven by the complementarity of high-skilled workers with computers (SBTC effect), rather than the substitutability of middle-skilled workers with computers (TBTC and apprenticeship effect).

The results linking employment polarization and a skill-specific labor force point to education/employment policies potentially tackling inequality (e.g., broad support of an apprenticeship style education system). However, the effects of slower technology adoption on growth and structural transformation should not be ignored, especially as more women enter the labor force. Women broadly favor service occupations, whereas apprentice employment has focused on male dominated industry occupations. This suggests that men would be shielded from polarization, but not women.

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A Model Appendix

This appendix provides additional model details, relevant derivations and formal proofs.

A.1 Environment and Equilibrium Details

First we complete the model environment from Section 2, then we derive the equilibrium allocations.

The market of machine production is perfectly competitive such that the price equals the marginal cost. The production of one machine requires $(1-\beta)$ units of the intermediate good $y_t(i)$. The price, $p_t^k(i,v) = p_t^k(i) = (1-\beta)p_t(i)$, follows from the zero-profit condition.

Producers of the final good are price takers and maximize profits, taking the price of their product ($p_t(i)$ normalized to one), wages ($w_{\ell t}$, w_{ht}) and the price of machines ($p_t^k(i,v)$) as given. The demand for intermediate machines of each vintage type (v) and for each intermediate good (i) is,

$$k_t(i,v) = \alpha_h \alpha_k(i) h_t(i).$$

The demand for machines at each production process i is,

$$k_t(i) = \int_0^{N_t} k_t(i,v)dv = \alpha_h \alpha_k(i) h(i) N_t. \tag{A.1}$$

Given the demand for machines and Lemma 1, the production of good $y_t(i)$ is,

$$y_t(i) = \alpha_\ell(i)\ell_t(i) \quad if \;\; 0 \leq i < J_t$$
$$y_t(i) = \alpha_h \alpha_k(i) h_t(i) N_t \quad if \;\; J_t \leq i \leq 1.$$

For any equilibrium, the marginal product of each skill group must be equalized across all goods produced. This means price differences must exactly offset productivity differences,

$$p_t(i)\alpha_\ell(i) = p_t(i')\alpha_\ell(i') := P_{\ell t}, \tag{A.2}$$

and

$$p_t(i)\alpha_h \alpha_k(i) = p_t(i')\alpha_h \alpha_k(i') := P_{ht}. \tag{A.3}$$

Due to the Cobb-Douglas production function, expenditures, $p_t(i)x_t(i)$, are equalized across all goods, which implies that the low- and high-skilled are equally distributed across goods, $\ell_t(i) = \frac{L}{J_t}$ and $h_t(i) = \frac{H}{1-J_t}$. Hence, the following cost condition must hold in equilibrium,

$$\frac{P_{ht}HN_t}{1-J_t} = \frac{P_{\ell t}L}{J_t}.$$

Substituting prices from Equations (A.2) and (A.3) yields the "no arbitrage" condition, which pins down the equilibrium threshold.

A.2 Proof of the Apprentice Productivity Schedule (Condition 1)

Condition 1 is,

$$\begin{aligned}
\frac{d\frac{dJ_t}{d\ln(N_t)}}{d\lambda} &= \frac{\partial\frac{dJ_t}{d\ln(N_t)}}{\partial J_t}\frac{dJ_t}{d\lambda} + \frac{\partial\frac{dJ_t}{d\ln(N_t)}}{\partial\lambda} \\
&= \frac{d^2J_t}{dJ_t d\ln(N_t)}\frac{dJ_t}{d\lambda} - \left(\frac{dJ_t}{d\ln(N_t)}\right)^2\frac{\partial^2\ln(\alpha_\ell(J_t))}{dJ_t d\lambda} \\
&= -\left(\frac{dJ_t}{d\ln(N_t)}\right)^2\left[\left(\frac{\partial^2\ln(\alpha_\ell(J_t))}{dJ_t^2} + \frac{1-2J}{(J_t(1-J_t))^2}\right)\left(\frac{-1}{\hat{\alpha}_\ell(J_t)}\frac{d\hat{\alpha}_\ell(J_t)}{d\lambda}\frac{dJ_t}{d\ln(N_t)}\right) + \right. \\
&\quad \left. \frac{\partial^2\ln(\alpha_\ell(J_t))}{dJ_t d\lambda}\right].
\end{aligned}$$

Proof. From the threshold cross-derivative, under Assumption 2, the negative threshold growth accelerates as the threshold decreases,

$$\frac{d^2J_t}{d\ln(N_t)dJ_t} = -\left(\frac{dJ_t}{d\ln(N_t)}\right)^2\left(\frac{\partial^2\ln(\alpha_\ell(J_t))}{\partial J_t^2} + \frac{1-2J}{(J_t(1-J_t))^2}\right) > 0 \;\text{ for all }\; J_t > J^\star. \tag{A.4}$$

From Equation (A.4), we know that the critical threshold value, $J^\star$, is such that,

$$\left(\frac{\partial^2\ln(\alpha_\ell(J_t))}{dJ_t^2} + \frac{1-2J_t}{(J_t(1-J_t))^2}\right) < 0.$$

By Assumptions 2 the first term in brackets is always negative. The critical threshold value lies in the lower-half of the unit-interval, $J^\star \in \left[0, \frac{1}{2}\right)$, since for any value $J^\star \geq \frac{1}{2}$ the expression is unambiguously negative. The critical threshold is the solution to,

$$-\frac{\partial^2\ln(\alpha_\ell(J^\star))}{d(J^\star)^2}(J^\star(1-J^\star))^2 + 2J^\star - 1 = 0.$$

Therefore, Condition 1 is satisfied when,

$$\left(\frac{\partial^2 \ln(\alpha_\ell(J_t))}{dJ_t^2} + \frac{1-2J}{(J_t(1-J_t))^2}\right)\frac{1}{\hat{\alpha}_\ell(J_t)}\frac{d\hat{\alpha}_\ell(J_t)}{d\lambda}\frac{dJ_t}{d\ln(N_t)} > \frac{\partial^2 \ln(\hat{\alpha}_\ell(J_t))}{dJ_t d\lambda}. \tag{A.5}$$

The left hand side is strictly positive as long as $J_t > J^\star$. The condition holds whenever $\frac{\partial^2 \ln(\hat{\alpha}_\ell(J_t))}{dJ_t d\lambda} < 0$. □

A.3 Proof of Apprentice Productivity (Equation (9))

There are two cross derivatives: (1) machine adoption and (2) routine displacement.

Machine Adoption across Regions

Proof. From Equation (5), the first term of Equation (9) is,

$$\begin{aligned}\frac{\partial\left(\frac{\partial \ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t} &= \left[\frac{dJ_t}{d\ln(N_t)}\left(\frac{1}{\overline{x}-J_t}+\frac{1}{1-J_t}\right) - \frac{d^2 J_t}{d\ln(N_t)dJ_t}\right] \\ &\quad \times\left(\frac{1}{\overline{x}-J_t}-\frac{1}{1-J_t}\right) < 0.\end{aligned}$$

The first term in brackets is negative (Equation (4)) and the second term is positive (Equation (A.4) with $J_t > J^\star$). The second term of Equation (9), the direct effect, is

$$\frac{\partial\left(\frac{\partial \ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial \lambda} = -\left(\frac{1}{\overline{x}-J_t}-\frac{1}{1-J_t}\right)\left(\frac{dJ_t}{d\ln(N_t)}\right)^2\left(-\frac{\partial^2 \ln(\hat{\alpha}_\ell(J_t))}{\partial J_t \partial\lambda}\right).$$

The sign of this expression depends on the exact $\hat{\alpha}_\ell(i)$-slope. Collecting terms, for Equation (9) to be negative, it must be that

$$\begin{aligned}&\left[\left(\frac{1}{\overline{x}-J_t}+\frac{1}{1-J_t}\right) + \left(\frac{\partial^2 \ln(\hat{\alpha}_\ell(J_t))}{dJ_t^2}+\frac{1-2J}{(J_t(1-J_t))^2}\right)\frac{dJ_t}{d\ln(N_t)}\right]\frac{1}{\hat{\alpha}_\ell(i)}\frac{d\hat{\alpha}_\ell(J_t)}{d\lambda} \\ &\qquad > \frac{\partial^2 \ln(\hat{\alpha}_\ell(J_t))}{\partial J_t\partial\lambda},\end{aligned}$$

which holds under Condition 1. □

Routine Displacement across Regions

Proof. The prove of routine displacement is analogous to machine displacement. That is, the first term from Equation (9) is,

$$\frac{\partial\left(\frac{\partial \ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t} = \frac{-\underline{x}(2J_t-\underline{x})}{J_t^2(J_t-\underline{x})^2}\frac{dJ_t}{d\ln(N_t)} + \frac{\underline{x}}{J_t(J_t-\underline{x})}\frac{d^2 J_t}{d\ln(N_t)dJ_t} > 0.$$

The second effect is negative and the first is positive for all $J_t > J^\star$, making the first term unambiguously positive. The direct effect on routine displacement is,

$$\frac{\partial\left(\frac{\partial \ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial \lambda} = \frac{\underline{x}}{J_t(J_t-\underline{x})}\left(\frac{dJ_t}{d\ln(N_t)}\right)^2\left(-\frac{\partial^2 \ln(\hat{\alpha}_\ell(J_t))}{dJ_t d\lambda}\right).$$

The algebraic sign depends on the exact $\hat{\alpha}_\ell(i)$-slope. Collecting terms, for Equation (9) to be positive, it must be that

$$\left[\left(\frac{(2J_t-\underline{x})}{J_t(J_t-\underline{x})}\right) + \left(\frac{\partial^2 \ln(\hat{\alpha}_\ell(J_t))}{dJ_t^2} + \frac{1-2J}{(J_t(1-J_t))^2}\right)\frac{dJ_t}{d\ln(N_t)}\right]\frac{1}{\hat{\alpha}_\ell(i)}\frac{d\hat{\alpha}_\ell(J_t)}{d\lambda} > \frac{\partial^2 \ln(\hat{\alpha}_\ell(J_t))}{dJ_t d\lambda},$$

which is always true under Condition 1. □

B Data Appendix

B.1 The SIAB Regional File 1975-2008

The SIAB is a two percent representative random sample of the German workforce collected by the Institute for Employment Research (IAB). It covers all currently employed individuals that are subject to social security payments for the years 1975 to 2008. It excludes the self-employed, civil servants, individuals in military service and students. Marginally employed individuals are only considered after 1999.

B.1.1 Sample Selection and Variable Description

Employment. The sample is restricted to males and females in West Germany. We drop individuals whose employment status is coded as "doing an apprenticeship/traineeship/internship" or those that have an undefined employment status. Hours worked information is not provided, except for a part-time versus full-time variable, hence part-time workers are re-weighted by two-thirds, as in Dustmann et al. (2009).

Table B.1: Descriptive Statistics 1979 and 2008 across Regions

	1979	2008
RTI Share	0.359 (0.061)	0.293 (0.055)
Routine Share	0.366 (0.064)	0.286 (0.061)
Manual Share	0.382 (0.055)	0.316 (0.056)
Abstract Share	0.340 (0.044)	0.427 (0.047)
PC Share		0.475[a] (0.044)
Service Share	0.420 (0.095)	0.602 (0.096)
Low Service Share	0.183 (0.029)	0.221 (0.029)
Apprentice Share	0.630 (0.043)	0.584 (0.033)
Female Share	0.363 (0.044)	0.443 (0.035)
Immigrant Share	0.072 (0.041)	0.060 (0.030)
Young Share	0.218 (0.038)	0.094 (0.016)
Age	37.1 (1.614)	42.5 (0.771)
Part-time Share	0.077 (0.020)	0.318 (0.036)

Education. The education variable is based on extrapolated data following imputation *method 1* in Fitzenberger et al. (2006). The high-skilled are defined as workers who graduated from university or college. Apprentices are classified as individuals that obtained an apprenticeship degree within the same broad sector (of services or non-services) they currently work in.

Wages. For ranking occupations, mean wages for each occupation in 1979 are used. We only consider full-time workers for the ranking. Since wages are top-coded, censored wages are impute by a fixed factor of 1.2 (Dustmann et al., 2009).

B.1.2 Descriptive Statistics

Table B.1 shows the (unweighted) mean and standard deviation of the main variables used. As expected, routine shares decrease over time, while abstract shares increase. The share

Table B.2: Employment Shares by Broad Occupation Class

	Employment Shares		Employment Changes	
Occupation Class	1979	2008	Δ_{79-08}	$Growth_{79-08}$
Managers	0.023	0.031	0.008	33.4%
(Semi-)Professionals	0.043	0.092	0.049	113.8%
Technicians/Engineers	0.069	0.074	0.006	8.1%
Commercial/Administration	0.261	0.302	0.042	16.0%
Production/Craft	0.411	0.267	-0.144	-35.0%
Agricultural occupations	0.010	0.012	0.001	14.0%
Services	0.183	0.222	0.038	20.9%

of service sector employment increases, as well as the share of female workers and the share of workers in part-time work (highly correlated with female labor market participation). Average age increases due to demographic transition coupled with higher university attendance rates.

Table B.2 computes changes in broad occupation employment shares over time. The middle of the skill distribution, *Production/Craft*, falls over time. Unlike the US, most of the fall in production has been absorbed by a rise in professional employment and not in services.

Using the same occupation classification, Table B.3 computes average task measures of the routine, manual and abstract components. In line with the theory and empirical results, occupations with the largest employment fall are the most routine-intensive occupations. Occupations with the largest increase are abstract.

B.2 The Qualification and Career Survey

The QCS is a representative survey of employees carried out by the BiBB and the IAB. It contains four cross-sections, in 1979, 1985/86, 1991/92 and 1998/99, where each covers about 30,000 individuals. We use these datasets from 1979 and 1999 to construct the

Table B.3: Tasks by Broad Occupation Class

Occupation Class	*RTI*	Routine	Manual	Abstract
Managers	0.379	4.450	2.523	6.021
(Semi-)Professionals	0.358	4.318	3.051	6.125
Technicians/Engineers	0.408	5.105	3.852	5.451
Commercial/Administration	0.413	4.678	2.912	5.196
Production/Craft	0.477	6.433	5.903	4.091
Agricultural occupations	0.407	4.891	5.002	4.614
Services	0.438	5.197	4.532	4.380

computer utilization measures (see Section 3.3) and occupation-specific task measures.

To construct occupation-specific task intensities we use the QCS 1979 survey, since this should reflect "initial" task requirements prior to computerization (for further details see Spitz-Oener, 2006). Similar to the US DOT measures, four measures are computed from the QCS:

1. *Routine task* as measured by how often single work steps repeat - classified from 1 to 5, i.e. from very repetitive to not at all.

2. *Manual task* as measured by the intensity of dexterity ("Handgeschick und Fingerfertigkeit") - on a scale from 1 to 5, from "(almost) always required" to "hardly any dexterity required."

3. *Non-routine interactive task* based on the intensity of required planning and coordination skills - on a scale from 1 to 5, from very intense in coordination requirements to not at all.

4. *Non-routine analytic task* as measured by the occupations' math requirements - classified into five categories from very basic arithmetic operations to very advanced arithmetic knowledge including differential calculus, integrals and algebra.

SUPPLEMENTAL ONLINE APPENDIX

NOT FOR PUBLICATION

O Empirical Online Appendix

This empirical appendix provides additional robustness tests of: (1) computer adoption using the actual PC shares in 1979; and (2) routine-labor displacement with additional controls.

Table O.1: **PC Adoption and Tasks**

	Dep. Variable: Δ PC share 1979-1999					
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.440***	-0.490***				
	(0.094)	(0.089)				
Routine			-0.455***	-0.498***	0.199**	0.134**
			(0.068)	(0.060)	(0.083)	(0.043)
Abstract					0.895***	0.891***
					(0.083)	(0.041)
Manual					-0.064	0.017
					(0.052)	(0.059)
State FE	No	Yes	No	Yes	No	Yes
N	182	182	182	182	182	182
R^2	0.353	0.496	0.472	0.594	0.713	0.775

Notes: Standard errors are clustered at the state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Table O.2: **PC Adoption, Apprentices and Tasks**

	Dep. Variable: Δ PC share 1979-1999			
	(1)	(2)	(3)	(4)
ARoutine	0.090	0.007	0.120	0.015
	(0.209)	(0.204)	(0.219)	(0.206)
ORoutine	0.193*	0.144*	0.207**	0.145**
	(0.085)	(0.066)	(0.090)	(0.056)
AAbstract	0.663***	0.693***		
	(0.113)	(0.146)		
OAbstract	1.273***	1.225***		
	(0.252)	(0.271)		
Abstract			0.908***	0.907***
			(0.094)	(0.062)
Manual	-0.059	0.026	-0.045	0.043
	(0.058)	(0.067)	(0.078)	(0.091)
State FE	No	Yes	No	Yes
N	182	182	182	182
R^2	0.736	0.791	0.713	0.776

Notes: Standard errors are clustered at the state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Table O.3: **Routine Displacement and Tasks with Controls**

	Dep. Variable: Δ RTI							
	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RTI	-0.188**	-0.086	-0.165**	-0.068	-0.107*	-0.107**	-0.075*	-0.354***
	(0.062)	(0.061)	(0.054)	(0.039)	(0.054)	(0.045)	(0.039)	(0.074)
High-skill	-0.281***							-0.211***
	(0.059)							(0.061)
Low-skill		0.042						0.054
		(0.077)						(0.057)
Service			-0.070***					-0.117***
			(0.015)					(0.019)
Female				0.036				0.093
				(0.029)				(0.051)
Immigrant					-0.170**			-0.091
					(0.055)			(0.049)
Young						0.189***		0.051
						(0.046)		(0.049)
Part-time							0.088	-0.0223
							(0.053)	(0.063)
N	546	546	546	546	546	546	546	546
R^2	0.363	0.310	0.321	0.310	0.348	0.337	0.315	0.403

Notes: Standard errors are clustered at the state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Table O.4: **Routine Displacement, Apprentices and Tasks with Controls**

	Dep. Variable: Δ RTI							
	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$	$\Delta^{(t+10)-t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ARTI	0.010	0.019	-0.111	0.011	0.036	-0.001	0.011	-0.131
	(0.130)	(0.134)	(0.150)	(0.129)	(0.116)	(0.124)	(0.132)	(0.104)
ORTI	-0.219***	-0.254***	-0.331***	-0.221***	-0.215***	-0.224***	-0.227***	-0.395***
	(0.052)	(0.057)	(0.070)	(0.054)	(0.052)	(0.051)	(0.056)	(0.065)
High-skill	-0.271***	-0.273***	-0.283***	-0.272***	-0.200***	-0.232***	-0.290***	-0.203***
	(0.057)	(0.052)	(0.060)	(0.060)	(0.039)	(0.046)	(0.069)	(0.055)
Low-skill		0.080						0.089*
		(0.051)						(0.047)
Service			-0.080***					-0.109***
			(0.017)					(0.016)
Female				-0.00771				0.0691
				(0.0289)				(0.0413)
Immigrant					-0.103*			-0.106*
					(0.046)			(0.047)
Young						0.117***		0.034
						(0.032)		(0.046)
Part-time							-0.043	-0.026
							(0.060)	(0.063)
N	546	546	546	546	546	546	546	546
R^2	0.371	0.375	0.386	0.371	0.382	0.380	0.372	0.411

Notes: Standard errors are clustered at the state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.