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Trade, Tasks, and Training: The Effect of Offshoring on Individual Skill Upgrading

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Abstract

We offer a theoretical explanation and empirical evidence for a positive link between increased offshoring and individual skill upgrading. Skill upgrading takes the form of on-the-job training, complementing the existing literature, which mainly focuses on the retraining of workers after a direct job displacement through offshoring. To establish a link between offshoring and on-the-job training, we introduce an individual skill upgrading margin into the small-open-economy version of the Grossman and Rossi-Hansberg (2008) model of offshoring. In our model offshoring, by scaling up workers' wages, creates previously unexploited skill upgrading possibilities and, thus, leads to more on-the-job training. Using data from German manufacturing, we find strong empirical support for the prediction that increased offshoring is positively related to individual on-the-job training participation.

JEL-Classification: F10, F16, F61
Keywords: Offshoring, Tasks, Skill upgrading, On-the-job training

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1 Introduction

It is a common feature of advanced economies that their workforces are increasingly engaged in the performance of more complex production tasks. Along with this changing structure of skill requirements, individuals constantly retrain and update their capabilities. According to Eurofound's European Working Conditions Survey 2010 (cf. Eurofound, 2012), industry-wide on-the-job training rates in Germany have increased from on average 28.4% in 2005 to about 40% in 2010. At the same time, more and more firms find it optimal to restructure their production processes by relocating the performance of offshorable tasks to low-wage countries abroad. Data from the OECD STAN bilateral trade data base show that the output share of intermediate imports from non-OECD countries in German manufacturing has increased by a remarkable 62% over the same time span. In this paper, we argue that both phenomena are linked. We offer a theory to explain the mechanism behind this link and an empirical analysis to show its significance and magnitude.

In general a positive link between offshoring and training should not come as a surprise since offshoring, which is associated with the relocation of tasks to low-wage countries abroad, in the end (at least temporary) displaces some workers from their jobs. As shown by Hummels et al. (2012), workers who are displaced because of offshoring have a particularly high probability to acquire vocational training during the subsequent period of transitional unemployment. We add to this literature, focusing instead on the impact that offshoring has on currently *employed* individuals and not only on those who directly loose their job through offshoring. This new focus is motivated by two facts: On the one hand, the number of workers, which are directly displaced from their job by offshoring, is dwarfed by the mass of individuals, which stay in their job.[1] On the other hand, it is well known from the theoretical trade literature that offshoring not only leads to direct job losses for workers whose tasks are shifted abroad, but also has a (positive) *productivity effect*, which may benefit *all* workers, as firms pass through productivity gains from offshoring to domestic workers in form of higher wages (Kohler, 2004; Grossman and Rossi-Hansberg, 2008; Rodríguez-Clare, 2010). It is exactly this productivity effect which in our theoretical model creates incentives for on-the-job training by increasing the associated wage gain of workers beyond the cost of skill upgrading.

To structure our idea, we set up a small-open-economy model of offshoring in the spirit of Grossman and Rossi-Hansberg (2008), featuring two offshorable sets of tasks, which differ in their skill requirements. Unlike in standard trade models, where endowments are fixed, workers in our model may react to a given offshoring shock by selecting into costly on-the-job training,

[1]For example, in the sample of Hummels et al. (2013), only 9% of all workers observed from 1998 to 2006 loose their job through mass-layoff events. Out of those layoffs, again only 10% can be associated with increased offshoring by the respective employers.

thereby gaining abilities that are needed to perform skill-intensive high-wage tasks. Since the productivity effect of offshoring (cf. Grossman and Rossi-Hansberg, 2008) proportionally scales up wages for both task sets, the gap between these wages increases as well, rendering on-the-job training more attractive for untrained workers, who select into skill upgrading as long as the (offshoring induced) gap in wages exceeds the associated cost of skill upgrading.

Focusing on this training indifference condition we translate our theoretical model into an empirically testable specification. We thereby – in line with our theoretical results – expect that offshoring leads to more observed on-the-job training at the individual level – a relationship that we can estimate within a standard Probit framework. Our offshoring variable thereby relates to sectoral imports of intermediate products, which are a widely used measure to proxy for industry-level offshoring in the empirical trade literature (cf. Feenstra and Hanson, 1996, 1999; Geishecker and Görg, 2008; Baumgarten et al., 2013). Using the industry-level variation in our offshoring measure to identify the impact on individual skill upgrading has the clear advantage that offshoring growth can be seen as *exogenous* to single workers, whose individual training decisions should not feed back into industry-level offshoring growth rates. This approach embeds our analysis into a recent and growing literature, which uses industry-level variation in globalization measures to identify effects that arise at the individual level (cf. Geishecker and Görg, 2008; Baumgarten et al., 2013; Ebenstein et al., 2013). Data on individual skill upgrading decisions come from the "BIBB/BAuA Employment Survey 2005/06", which holds detailed information on individual participation in on-the-job training measures. Crucially, due to the high resolution of our data we can take into account a wide range of control variables, which in the empirical training literature (cf. Arulampalam et al., 2004; Bassanini et al., 2007) already have been identified as major determinants of individual skill-upgrading decisions. Of particular interest for our application is thereby the possibility to observe the introduction of technological innovations directly at the workplace, which gives us the opportunity to separate the effect of offshoring from the one of sectoral biased technological change (cf. Feenstra, 2010).

Our findings offer clear support for the mechanism laid out in our theoretical model. Offshoring growth has a positive and significant impact on the individual on-the-job training propensity of workers employed in German manufacturing between 2004 and 2006. This link holds for a number of specifications and is robust to the inclusion of various controls at the individual, firm, and industry level. After taking account of, among other things, technological change, business cycle effects, and firm-size differences, a one standard deviation higher offshoring growth at the industry level over the period 2004 to 2006 is related to an increase in the propensity to observe individual on-the-job training by between 3 to 7 percentage points.

Our paper connects two strands of the empirical literature, which so far mostly have been analysed in complete isolation. On the one hand we contribute to a literature that seeks to identify the determinants of individual on-the-job training decisions (see Bassanini et al. (2007) for an overview). On the other hand, we also add to the empirical trade literature, which focuses on the implications that offshoring has for domestic labour markets (see Baumgarten et al. (2013); Ebenstein et al. (2013) for recent examples). The first strand of the literature usually focuses on a combination of product and/or labor market based explanations to explain individual on-the-job training decisions in a closed-economy setting, thereby ignoring the impact that globalization may have on individual training decisions.[2] The empirical trade literature, on the contrary, mainly is concerned with the impact that offshoring has on skill upgrading in the aggregate. As a central result, several studies have shown that increased offshoring is associated with a rise in the share of high-skilled employment in total employment (cf. Crinò, 2008; Feenstra, 2010; Davies and Desbordes, 2012). Individual skill levels thereby usually are considered as fixed such that all skill upgrading takes place at the *extensive* margin between rather than at the *intensive* margin within workplaces. As a notable exception Hummels et al. (2012) show that workers, who are directly displaced from their job through offshoring are more likely to select into training measures before taking up a new job. We complement this research by focusing on the vast majority of workers staying in their jobs that, hence, are indirectly affected through the general-equilibrium effects of offshoring – effects to which they respond by increased on-the-job training.

The paper is structured as follows. In the next section, we develop our theoretical model and derive as main prediction that offshoring growth leads to more individual skill upgrading. Subsequently, we look for the proposed link in the data and present an empirical analysis, which includes a description of the econometric set-up, the data used, the results obtained and a discussion on the timing and the robustness of the link between offshoring and on-the-job training. A final section concludes the paper.

2 A simple model of offshoring and on-the-job training

The goal of this section is to describe an intuitive mechanism, which links offshoring and on-the-job training. To this end, we employ a simplified version of the Grossman and Rossi-Hansberg (2008) model of trade in tasks, focusing on a single industry, which produces a homogeneous, constant returns to scale output Y at a given world market price normalised to $p \overset{!}{=} 1$. The production of final output Y requires the performance of two task sets, $\widetilde{S}$ and $\widetilde{N}$, such that

[2] Arulampalam et al. (2004) and Bassanini et al. (2007) control for a comprehensive range of individual-level indicators to explain the selection of workers into on-the-job training. Méndez and Sepúlveda (2012) point to the influence of the business cycle on skill upgrading and discuss carefully the different training-types and their respective business cycle properties. Additionally, Görlitz and Stiebale (2011) look at industry-level competition as a driver of on-the-job training decisions.

our production technology may be summarized by $Y = F(\widetilde{S}, \widetilde{N})$, with $\widetilde{S}$ and $\widetilde{N}$ replacing the usual inputs in the otherwise standard neoclassical production function $F(\cdot)$. The task sets, $\widetilde{S}$ and $\widetilde{N}$, differ in their skill requirements: While workers performing the $\widetilde{S}$-set must have some task-specific skills, no such skills are needed to perform tasks from the $\widetilde{N}$-set. For simplicity, we furthermore assume that both tasks sets consist of only two tasks: A non-offshorable task, S or N, and an offshorable task, S^* or N^*, which are combined according to technologies, $\widetilde{S} = \widetilde{S}(S, S^*)$ and $\widetilde{N} = \widetilde{N}(N, N^*)$.

The offshorable tasks, S^* or N^*, will be performed abroad, if the cost of doing so are sufficiently low, i.e. if $w_S \geq \tau_S w_S^*$ and $w_N \geq \tau_N w_N^*$, with $\tau_S, \tau_N \geq 1$ denoting the usual iceberg-type offshoring cost and w_S^* and w_N^* being the (constant) unit cost of performing the tasks S^* and N^* at a low-cost location abroad. The unit-costs for the task sets, $\widetilde{S}$ and $\widetilde{N}$, may then be written as $\omega_S(w_S, \tau_S w_S^*) = \Omega_S w_S$ and $\omega_N(w_N, \tau_N w_N^*) = \Omega_N w_N$, where $\Omega_S \equiv \omega_S(w_S, \tau_S w_S^*)/w_S \leq 1$ and $\Omega_N \equiv \omega_N(w_N, \tau_N w_N^*)/w_N \leq 1$ are defined as the cost savings factors from relocating tasks S^* or N^* abroad (cf. Grossman and Rossi-Hansberg, 2008). Analogously, the unit cost for final output Y may be expressed as $c(\Omega_S w_S, \Omega_N w_N) = \gamma c(w_S, w_N)$, with $\gamma \equiv c(\Omega_S w_S, \Omega_N w_N)/c(w_S, w_N) \leq 1$ denoting the total cost savings factor from (partly) offshoring both inputs used in $Y = F(\widetilde{S}, \widetilde{N})$.

We assume a homogeneous workforce of size $\bar{L} > 0$. Workers can either exclusively perform tasks from the $\widetilde{S}$-set or from the $\widetilde{N}$-set, whereas, as outlined above, tasks from the $\widetilde{S}$-set require task-specific skills, while no such requirement exists for tasks from the $\widetilde{N}$-set. To acquire the skills needed for the performance of tasks from the $\widetilde{S}$-set, workers have to invest in costly on-the-job training. Training cost $\kappa > 0$ (paid in units of the *numéraire*) are assumed to be constant and workers invest into on-the-job training as long as the wage gain $w_S - w_N$ associated with it exceeds the corresponding cost κ. Accordingly, we may write the net gain from on-the-job training as

$$u \equiv w_S - w_N - \kappa \geq 0, \tag{1}$$

keeping in mind that in equilibrium $u = 0$ must hold, leaving workers indifferent between both alternatives.

Equilibrium wages under autarky (denoted by superscript a) and with offshoring (denoted by superscript o) can now be found in the intersection point of the training indifference condition Eq. (1) and the zero profit condition $\gamma c(w_N, w_S) = 1$ (see figure 1 below). As outlined above, $\gamma \leq 1$ thereby represents the total cost savings factor from offshoring, being equal to one under autarky and smaller than one in an equilibrium with offshoring.

In order to derive testable predictions on how offshoring alters wages and thus the training decision in Eq. (1), we have to specify our simple model in more detail. We assume that Y follows from a Cobb Douglas production technology, such that $F(\widetilde{S}, \widetilde{N}) = \widetilde{S}^\alpha \widetilde{N}^{1-\alpha}$ with $\alpha \in (0, 1)$. It then can be shown that the total cost savings from offshoring $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha} \leq 1$ are a weighted geometric mean of the cost savings at the task level, $\Omega_S \leq 1$ and $\Omega_N \leq 1$, respectively. The technology, according to which tasks within each of the two task sets are bundled together, is the same as in Antras and Helpman (2004) and Acemoglu and Autor (2011). Assuming $\widetilde{S}(S, S^*) = BS^{\theta}(S^*)^{1-\theta}$ as well as $\widetilde{N}(N, N^*) = BN^{\theta}(N^*)^{1-\theta}$, with $\theta \in (0, 1)$ measuring the cost share of non-offshorable tasks and $B \equiv 1/[\theta^{\theta}(1-\theta)^{1-\theta}] > 0$ being a positive constant, we can infer that the cost savings from offshoring at the task-level, $\Omega_S = (\tau_S w_S^*/w_S)^{1-\theta} \leq 1$ and $\Omega_N = (\tau_N w_N^*/w_N)^{1-\theta} \leq 1$, are proportional to the respective international wage differential (including the transport costs τ_S or τ_N, respectively). An offshoring firm's profit maximization problem may hence be written as

$$\pi = \max_{\widetilde{S}, \widetilde{N}} \; F(\widetilde{S}, \widetilde{N}) - \Omega_S w_S \widetilde{S} - \Omega_N w_N \widetilde{N},$$

from which the corresponding first order conditions can be derived as

$$w_S(\tilde{s}) = f'(\tilde{s})/\Omega_S, \tag{2}$$

$$w_N(\tilde{s}) = [f(\tilde{s}) - \tilde{s}f'(\tilde{s})]/\Omega_N, \tag{3}$$

with $f(\tilde{s}) \equiv F(\widetilde{S}, \widetilde{N})/\widetilde{N} = \tilde{s}^{\alpha}$ referring to our production function in intensive form notation and $\tilde{s} \equiv \widetilde{S}/\widetilde{N}$ measuring the *overall* skill intensity in the entire production process (including domestic tasks, S and N, as well as foreign tasks, S^* and N^*).

From Eqs. (2) and (3), two channels through which offshoring affects domestic wages can be identified. As in Grossman and Rossi-Hansberg (2008), cost savings from offshoring are handed through to domestic workers in form of higher wages, which due to the *productivity effect* of offshoring are scaled up by factors, $1/\Omega_S \geq 1$ and $1/\Omega_N \geq 1$, respectively. On the contrary, the *labor supply effect* of offshoring leads to disparate wage effects by driving a wedge between the overall skill intensity $\tilde{s} \equiv \widetilde{S}/\widetilde{N}$, which applies for the entire production process, and the domestic skill intensity $s \equiv S/N$, which only reflects the composition of the domestic workforce. To illustrate the labor supply effect, Shephard's Lemma can be applied to $\omega_S(w_S, \tau_S w_S^*)$ and $\omega_N(w_N, \tau_N w_N^*)$, resulting in:

$$\frac{\partial \omega_S(w_S, \tau_S w_S^*)}{\partial w_S} \equiv \frac{S}{\widetilde{S}} = \theta\Omega_S \quad \text{and} \quad \frac{\partial \omega_N(w_N, \tau_N w_N^*)}{\partial w_N} \equiv \frac{N}{\widetilde{N}} = \theta\Omega_N. \tag{4}$$

Dividing both expressions in Eq. (4) by each other reveals how the domestic skill intensity,

$s \equiv S/N$, is altered by the labor supply effect of offshoring, such that

$$\tilde{s} = \frac{\Omega_N}{\Omega_S} s, \tag{5}$$

emerges as the overall skill intensity. Intuitively, in the autarky equilibrium (with $\Omega_S = \Omega_N = 1$) the overall skill intensity coincides with the domestic skill intensity, implying $\tilde{s} = s$. With offshoring, the overall skill intensity additionally depends on which factor is offshored more intensively, such that $\tilde{s} \gtrless s$ if $N/\widetilde{N} \gtrless S/\widetilde{S}$. Intuitively, the labor supply effect of offshoring thereby favors the input factor which is offshored less intensively. When replacing $\tilde{s}$ in Eqs. (2) and (3) by Eq. (5) to determine the overall effect that offshoring has on domestic wages, it turns out that the productivity effect of offshoring is dominant and causes a proportional increase in *both* wages, $w_S^o(\tilde{s}) = w_S^a(s)/\gamma$ and $w_N^o(\tilde{s}) = w_N^a(s)/\gamma$, by the same factor $1/\gamma \geq 1$ for a notionally unchanged domestic factor intensity s.

To see the impact on workers' training decision, we may now substitute both wage rates into the training indifference condition (1), which then can be rewritten as:

$$u = w_S(s) - w_N(s) - \kappa = \frac{\alpha s^{\alpha-1} - (1-\alpha) s^{\alpha}}{\gamma} - \kappa, \tag{1'}$$

with $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha} < 1$ implying $s^o > s^a$. Intuitively, if both wages are scaled up by an identical factor $1/\gamma > 1$ the same holds true for the gap $w_S - w_N$ between these wages. In the end, as more and more domestic workers optimally react on $u > 0$ by upgrading their individual skills, the domestic skill intensity rises from s^a to s^o such that equilibrium is restored.

Figure 1 illustrates the effect of offshoring on on-the-job training. Starting out from the autarky equilibrium in A and holding the domestic skill intensity notionally fixed at $s = s^a$, offshoring causes a radial outward expansions of the unit-cost curve by factor $1/\gamma < 1$, which results in the hypothetical equilibrium B.[3] However, in point B we have $u > 0$, leaving domestic workers with an incentive to invest in on-the-job training. As more and more workers decide in favor of on-the-job training, the domestic skill intensity increases from s^a to s^o until the new (offshoring) equilibrium C is reached. This result is at the heart of our analysis and we frame it in the following Proposition.

[3]Fixing the domestic skill intensity at $s = s^a$ in this first step means that domestic workers are not allowed to switch tasks between the $\widetilde{N}$- and the $\widetilde{S}$-set. Of course this does not imply that workers are constrained in switching from offshorable N^*- or S^*-tasks to non-offshorable N- or S-tasks within the respective $\widetilde{N}$- or $\widetilde{S}$-set. Intuitively, the latter kind of task-arbitrage is a natural adjustment strategy to increased offshoring and a necessary condition for full-employment in our model.

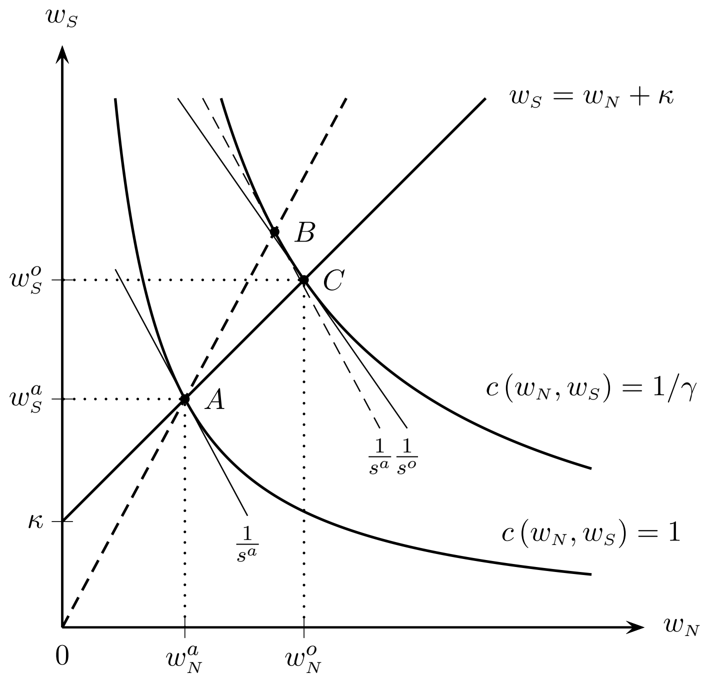

Figure 1: *On-the-job training with and without offshoring*

Proposition 1 *A decline in the cost of offshoring increases the share of tasks performed abroad, thereby leading to increased individual skill upgrading through on-the-job training.*

Proof Analysis in the text and formal discussion in Appendix 5.

Summing up, offshoring positively impacts the individual decision in favor of on-the-job training. Interestingly, the training decision does not depend on the task content of offshoring. Even if only one task type is relocated abroad, $\Omega_S < 1$ or $\Omega_N < 1$ will be sufficient to induce $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha} < 1$ and, thus, more on-the-job training. Also note that offshoring not only affects the skill upgrading decision of those individuals which are directly hit by a (temporary) job loss though offshoring (cf. Hummels et al., 2012). Rather it is the case that *all* individuals and in particular the vast majority of those who stay with their jobs are more likely to invest in individual skill upgrading as a response to given offshoring shock. Building upon these insights, we put Proposition 1 to the test by estimating the impact of increased industry-level offshoring on the individual on-the-job training decision displayed in Eq. (1).

3 The impact of offshoring on on-the-job training

The empirical part of our paper is structured as follows: We lay out our empirical strategy in Subsection 3.1. Subsection 3.2 describes the data we use. The results of our empirical analysis then follow in Subsection 3.3. Finally, Subsections 3.4 and 3.5 discuss the timing of offshoring and skill upgrading and offer further robustness checks.

3.1 Empirical strategy

As a natural starting point to test Proposition 1, recall training indifference condition (1), which for individual $i = 1, ..., I$ employed in industry $j = 1, ..., J$ can be rewritten as

$$u_{ij} = w_{Sij} - w_{Nij} - \kappa_{ij}.$$

We know from Proposition 1 that any increase in offshoring (triggered by a decline in the offshoring costs τ_S or τ_N) widens the gap between w_{Sij} and w_{Nij}, thereby making on-the-job training more attractive for the individual worker. What we seek to identify in our empirical analysis is the realized on-the-job training in response to a given offshoring shock. We thus identify the adjustment mechanism described in our model above, according to which individuals engage in on-the-job training after an offshoring shock until a new equilibrium with $u_{ij} = 0$ and $s^o > s^a$ is reached. Unfortunately, an individual's net gain u_{ij} from on-the-job training is unobservable to us. Yet, we know that individual i selects into on-the-job training (indexed by $U_{ij} = 1$) if $u_{ij} > 0$ and does not do so (indexed by $U_{ij} = 0$) if $u_{ij} \leq 0$. We are thus able to portray the probability of on-the-job training as the outcome of an underlying latent variable model

$$Pr(U_{ij} = 1 \,|\, \cdot) = Pr(u_{ij} > 0 \,|\, \cdot), \tag{6}$$

conditioning on a vector $(\cdot)$ of observable covariates. Our main variable of interest is the growth rate of offshoring, $\widehat{O}_j$, in industry j, which, according to Proposition 1, should have a positive impact on the probability of on-the-job training in Eq. (6). We furthermore allow the individual training decision to depend on individual- and industry-specific characteristics, which we collect in vectors $\mathbf{Y}_i$ and $\mathbf{X}_j$, respectively. While the vectors $\mathbf{Y}_i$ and $\mathbf{X}_j$ will be specified in more detail below, we may for now interpret them as additional controls capturing such things as heterogeneity in the training cost κ_{ij}. Taken together, we can reformulate the training decision in Eq. (1) as:

$$u_{ij} = \beta_0 + \beta\widehat{O}_j + \mathbf{X}_j'\boldsymbol{\delta} + \mathbf{Y}_i'\boldsymbol{\eta} + \varepsilon_{ij}, \tag{1''}$$

with $\varepsilon_{ij} \sim N(0,1)$ following a standard normal distribution with zero mean and variance one. We can then estimate the probability of on-the-job training $Pr(U_{ij} = 1 \,|\, \cdot)$ in Eq. (6) by a Probit model based on the following empirical specification:

$$Pr\,(U_{ij} = 1 \,|\, \cdot\,) = Pr\,(u_{ij} > 0 \,|\, \cdot\,) = Pr(\beta_0 + \beta\widehat{O}_j + \mathbf{X}_j'\boldsymbol{\delta} + \mathbf{Y}_i'\boldsymbol{\eta} > \varepsilon_{ij} \,|\, \cdot\,). \tag{6$'$}$$

In line with Proposition 1, we expect a positive effect of offshoring growth $\widehat{O}_j$ on the probability of observing individual on-the-job training, i.e. $\beta > 0$. The identification of this relationship in our empirical model (6′) comes from varying offshoring growth rates across industries in which individuals are employed. This has the clear advantage that offshoring growth, which is measured at the industry level j, can be seen as exogeneous to worker i, whose individual training decision should not feed back into sector level offshoring growth. Consequently, we do not expect reverse causality to play a major role as potential source of endogeneity in our setting. This approach embeds our analysis into a recent and growing literature which uses industry level variation in globalization measures to identify individual level effects (Geishecker and Görg, 2008; Ebenstein et al., 2013; Baumgarten et al., 2013). To limit the problem of omitted variables as another main reason for potentially biased estimates, we rely on a rich set of individual- and industry-specific covariates (summarized in $\mathbf{Y}_i$ and $\mathbf{X}_j$), which we introduce in Section 3.2 before discussing their role against the background of our empirical results in Section 3.3.

3.2 Data and definition of variables

Information on individual skill upgrading is taken from the "BIBB/BAuA Employment Survey 2005/06", which contains information on a wide set of workplace related variables for a representative sample of 20.000 individuals that participated between October 2005 and March 2006.[4] We use the latest available wave of what has become established as a reliable and detailed source for information related to on-the-job training (Acemoglu and Pischke, 1998; Dustmann and Schönberg, 2012). Our main dependent variable is the training incidence U_{ij}, which we define as follows: If a respondent stated that she participated in on-the-job training once or several times within the last two years or, alternatively, since being on her current job, we count either one as training incidence and set $U_{ij} = 1$. Otherwise we define $U_{ij} = 0$. The "BIBB/BAuA Employment Survey 2005/06" is particularly suited for our analysis since it combines detailed information on training participation with a rich set of individual controls that already have been identified as important determinants for the individual training decision (Bassanini et al.,

[4]The following version of the data set is used: Hall and Tiemann (2006) BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2006, SUF 1.0; Research Data Center at BIBB (ed.); GESIS Cologne, Germany (data access); Federal Institute of Vocational Education and Training, Bonn doi:10.4232/1.4820. For further details, also see Rohrbach (2009).

2007). In particular, we have information on demographic controls (age, gender, education) and workplace characteristics (firm size, tenure, employment contract).[5] In context of the recent offshoring literature (cf. Acemoglu et al., 2012), our data has the great advantage that we are able to observe the introduction of new technologies and organizational changes at the workplace. This allows us to discriminate between offshoring and technological change when explaining the variation in individual training decisions, and eliminates possible concerns about technological change being a potential source of an omitted variable bias. As another advantage of our data we have information on individual job loss fears (cf. Geishecker et al., 2012). Given that offshoring often is associated with job losses for some workers (usually followed by a period of transitory unemployment and/or training) this information provides a suitable control for a potential postponement of on-the-job training in favour of later out-of-the-job training activity, as for example identified by Hummels et al. (2012). To control for business cycle effects, which have been linked to training by Méndez and Sepúlveda (2012), we rely on workers' assessment of the employing firm's current business success, but also compute industry level output growth between 2004 and 2006. Finally, following Görlitz and Stiebale (2011) we also use Herfindahl indices of industry concentration from the German Monopoly Commission for 2003 to control for varying product market competition in different industries.

Offshoring is measured as a trade related phenomenon using data on imported intermediates.[6] In line with our identification strategy outlined above, we follow the literature and observe offshoring at the industry level (Ebenstein et al., 2013; Baumgarten et al., 2013). In particular, we stick to the concept of Geishecker and Görg (2008) and use input-output tables provided by the German Statistical Office to compute the share Θ_{jj^*} of intermediate products used in industry j that originate from the same industry j^* abroad. We then multiply Θ_{jj^*} by IMP_j, which is the total value of sector j's imports of goods that originate from non-OECD countries, and finally divide by Y_j, which is the value of sector j's output. In the end we obtain

$$O_j = \frac{\Theta_{jj^*} IMP_j}{Y_j}, \tag{7}$$

as a measure for the intensity of offshoring in sector j. Note that our offshoring measure only includes intermediates that are imported from the same sector abroad, resembling the "narrow"

[5] For sources, a comprehensive description, and more detailed summary statistics of the variables in our final sample please refer to the data appendix.

[6] Proxies for offshoring based on foreign direct investment (FDI) often suffer from the insufficient decomposability of this data with regard to the motive behind outbound foreign direct investments. As an exception in this literature, Davies and Desbordes (2012) are able to distinguish between greenfield FDI as well as mergers and acquisitions (M&A), which allows them to control for FDI motives such as technology acquisition or the elimination of foreign competitors.

concept of offshoring put forth in Feenstra and Hanson (1999).[7] Following our theoretical model from Section 2, we are interested in offshoring that results from a cost savings motive and, hence, focus only on imports of intermediates that originate from non-OECD countries.[8] After all, this gives us a measure of offshoring to non-OECD countries that varies across 22 manufacturing industries (according to the NACE 1.1 classification). We use this information to compute the sectoral growth rate of offshoring $\widehat{O}_j$ over the relevant sample period from 2004 to 2006. Both, levels and relative changes of our offshoring measure are reported in Table 5 (see Appendix 6). The levels can be considered as fairly low, which reflects the fact that trade with non-OECD countries only accounts for a small share in German imports. Yet, growth has been impressive. On average offshoring increased by 33% over the period from 2004 through 2006. To obtain our final estimation sample, we match the growth rate of our offshoring variable with the individual information taken from the "BIBB/BAuA Employment Survey 2005/06" and our further sectoral control variables. Focusing only on individuals holding a full time contract in one of the 22 manufacturing industries considered above leaves us with a total of 3.917 observations.

3.3 Estimation results

We estimate several variants of the Probit model specified in Section 3.1. Starting with Table 1, in which we provide first evidence on the link between offshoring growth and on-the-job training, we gradually add additional individual control variables, which the training literature has identified as major determinants of individual skill upgrading (see Bassanini et al., 2007).

As a point of reference, Column (1) in Table 1 shows the average marginal effect of offshoring growth from 2004 to 2006 on the probability of on-the-job training participation. According to this first estimate, offshoring growth has a strong and significant impact on individual skill upgrading: A doubling of the non-OECD offshoring intensity defined in Eq. (7) would lead to an increase in the probability of on-the-job training participation by 0.1732. Taking into account the immense offshoring growth of (on average) more than 30% in the German manufacturing between 2004 and 2006, we find that a sizeable shift in training participation can be attributed to increased offshoring.

Gradually adding further individual controls in the Columns (2) to (6) downsizes the effect of offshoring growth only marginally. However, in line with Bassanini et al. (2007) and Méndez and Sepúlveda (2012), we find the usual life-cycle pattern in the results in Column (2), according to which older individuals are less likely to undertake on-the-job training than their younger

[7] For a detailed discussion of the differences between the measure used here and the measure used by Feenstra and Hanson (1999) please refer to Geishecker and Görg (2008).

[8] See Grossman and Rossi-Hansberg (2012) a model of trade in tasks between similar countries, in which firms have incentives to cluster the production of the same tasks at the same location in the presence of external scale economies that operate at the country level.

Table 1: *Offshoring and on-the-job training: individual controls*

	(1)	(2)	(3)	(4)	(5)	(6)
Average marginal effect of:						
Offshoring growth	0.1732***	0.1643***	0.1570***	0.1565***	0.1549***	0.1500***
	(0.0534)	(0.0515)	(0.0490)	(0.0423)	(0.0415)	(0.0246)
Age 30 - 39		0.0351	0.0331	-0.0161	-0.0087	-0.0130
		(0.0228)	(0.0234)	(0.0254)	(0.0232)	(0.0199)
Age 40 - 49		-0.0142	-0.0132	-0.0855***	-0.0722**	-0.0691***
		(0.0280)	(0.0301)	(0.0290)	(0.0282)	(0.0242)
Age 50 - 64		-0.0964***	-0.0946***	-0.1970***	-0.1811***	-0.1725***
		(0.0330)	(0.0320)	(0.0280)	(0.0279)	(0.0247)
Age 65+		-0.3249***	-0.3257***	-0.4391***	-0.4214***	-0.4177***
		(0.0774)	(0.0788)	(0.0676)	(0.0665)	(0.0555)
female			-0.0630***	-0.0419**	-0.0393**	-0.0782***
			(0.0232)	(0.0200)	(0.0198)	(0.0176)
Married			-0.0100	-0.0148	-0.0147	-0.0112
			(0.0238)	(0.0235)	(0.0233)	(0.0226)
Tenure				0.0076**	0.0084**	0.0090**
				(0.0038)	(0.0039)	(0.0039)
Tenure squared				-0.0001	-0.0001	-0.0001
				(0.0001)	(0.0001)	(0.0001)
Medium-skill				0.1181***	0.1169***	0.0383
				(0.0372)	(0.0368)	(0.0350)
High-skill				0.2118***	0.2117***	0.0169
				(0.0255)	(0.0258)	(0.0204)
Importance to have a career					0.0628***	0.0651***
					(0.0199)	(0.0199)
KldB88 (2-digit) occupation FE	no	no	no	no	no	yes
Pseudo R-squared	0.0100	0.0199	0.0221	0.0492	0.0509	0.1133
Observations	3,917	3,917	3,917	3,917	3,917	3,888

Notes: The table shows average marginal effects from estimating variants of the Probit model specified in Section 3.1. The reference category for an individual's age is: age 16 - 29. Standard errors are clustered at the industry level and are shown in parentheses below the coefficients. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

counterparts. Including a gender indicator in Column (3), we find, that men are more likely to select into on-the-job training than women, which at a first sight contrasts with the findings of Arulampalam et al. (2004), who show that in the European context women are in general no less likely to participate in training than men. However, as documented in Bassanini et al. (2007), the effect of gender on training participation, crucially depends on the sector of employment, with woman receiving comparatively less on-the-job training in certain medium/low-tech manufacturing industries. Given that our sample only includes workers employed in manufacturing industries, with a strong bias towards male employment (on average 75.9%), we should not be surprised to find a negative gender coefficient. Marital status, which we also introduce in Column (3), has no significant effect on training participation. In Column (4) we additionally control for work experience and education. Tenure has a positive but small effect on the probability of training participation. We treat this result with caution, since tenure – for obvious reasons – most likely is endogenous (Bassanini et al., 2007). Turning to the education indicators, we find the usual result, that high-skilled workers are more likely to participate in training than medium-skilled workers, while medium-skilled workers are again more likely to participate in training than low-skilled workers (see Pischke, 2001; Bassanini et al., 2007). To control for usually unobservable heterogeneity among workers (e.g. motivation), we exploit the detailed information included in the "BIBB/BAuA Employment Survey 2005/06" and add a binary indicator variable, which takes the value of one if the individual stated that having a career is (very) important and a value of zero otherwise. As we would expect, individuals, which care more about their career, are also more likely to invest in individual skill upgrading. Finally, adding occupation fixed effects in Column (6) to account for occupation-specific variation in the data, leaves most of our coefficients unchanged.[9] Only the coefficients for education turn insignificant. This, however, does not come as a surprise, given that in Germany entry into most occupations is subject to strict skill requirements (e.g. holding a certain university degree or a specific vocational qualification). Taking into account the implied homogeneity of workers in terms of formal education within occupations, it is clear that any attempt to identify the education coefficients based on the remaining skill variation within occupations necessarily is doomed to fail. The necessity to control for occupation-specific effects in our context arises as interactivity and complexity in the job content of certain occupations impose severe limits to the offshorability of the respective jobs (Blinder, 2006; Goos et al., 2009; Ottaviano et al., 2013). At the same time, these activities may require more frequent skill updating, which we would not want to confuse with our skill upgrading mechanism from Section 2. Taking stock, we find that the effect of offshoring growth on on-the-job training participation is only marginally reduced if further control variables at the individual level are included.

In a next step we turn to more likely candidates for an omitted variable bias and control for characteristics, which either directly describe the individual workplace or link to the industry in which the respective worker is employed. We thereby keep our individual controls from Column (6) in Table 1 throughout, while gradually adding additional workplace- and industry-level control variables in Table 2.

We start with the inclusion of firm size controls in Column (1) of Table 2. In line with Bassanini et al. (2007), we find that workers employed by larger firms are more likely to undertake on-the-job training than workers in small firms. Given that offshoring usually is highly concentrated among large firms, with small firms often doing no offshoring at all (see Moser et al., 2009; Hummels et al., 2013), we would expect that our estimate is upward biased, if differences in firm size are not taken into account. Indeed, when controlling for differences in firm size, we find that the impact that offshoring growth has on the probability of individual skill

[9] By adding occupation fixed effects we lose 29 observations for which either no occupational classification is coded in the data or too few observation for the estimation of an occupation-specific effect exist.

Table 2: *Offshoring and on-the-job training: workplace and sectoral controls*

	(1)	(2)	(3)	(4)	(5)	(6)
Average marginal effect of:						
Offshoring growth	0.1110***	0.1107***	0.1060***	0.1078***	0.1043***	0.0776***
	(0.0253)	(0.0253)	(0.0253)	(0.0257)	(0.0264)	(0.0201)
Firm size 10 - 49	-0.0036	-0.0006	-0.0148	-0.0191	-0.0147	-0.0187
	(0.0225)	(0.0216)	(0.0216)	(0.0218)	(0.0216)	(0.0214)
Firm size 50 - 249	0.0701***	0.0759***	0.0537***	0.0488***	0.0537***	0.0496***
	(0.0170)	(0.0150)	(0.0162)	(0.0166)	(0.0161)	(0.0163)
Firm size 250 - 499	0.1241***	0.1306***	0.1051***	0.0990***	0.1049***	0.0973***
	(0.0303)	(0.0288)	(0.0278)	(0.0272)	(0.0279)	(0.0281)
Firm size 500+	0.1518***	0.1584***	0.1343***	0.1273***	0.1343***	0.1190***
	(0.0284)	(0.0273)	(0.0267)	(0.0253)	(0.0266)	(0.0243)
Fixed term contract		-0.0901***	-0.0730**	-0.0765**	-0.0730**	-0.0785**
		(0.0323)	(0.0318)	(0.0320)	(0.0319)	(0.0328)
Temporary work		0.0272	0.0557	0.0512	0.0571	0.0394
		(0.0532)	(0.0538)	(0.0532)	(0.0535)	(0.0539)
Job loss fear		-0.0621***	-0.0632***	-0.0470**	-0.0634***	-0.0504**
		(0.0204)	(0.0208)	(0.0207)	(0.0209)	(0.0211)
New technology introduced			0.1674***	0.1655***	0.1676***	0.1640***
			(0.0219)	(0.0218)	(0.0218)	(0.0214)
Current Firm success (very) good				0.0429**		0.0406**
				(0.0200)		(0.0192)
Industry level output growth					-0.0614	
					(0.0993)	
Industry level Herfindahl index						0.0006***
						(0.0001)
Individual controls	yes	yes	yes	yes	yes	yes
KldB88 (2-digit) occupation FE	yes	yes	yes	yes	yes	yes
Pseudo R-squared	0.1240	0.1271	0.1359	0.1369	0.1360	0.1391
Observations	3888	3888	3888	3888	3888	3888

Notes: The table shows average marginal effects from estimating variants of the Probit model specified in Section 3.1. The reference category for firm size is 1 - 9 employees. The industry output growth is computed for 2004 to 2006. The Herfindahl index, which is published bi-annually by the German Monopoly Commission refers to 2005. Individual controls are the same as in Column (6) of Table 1. Standard errors are clustered at the industry level and shown in parentheses below the coefficients. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

upgrading is reduced, although still positive and highly significant. In Column (2) of Table 2 we add further controls, which directly describe the employees' individual working environments. In particular we take into account whether a worker is employed under a fixed term contract or through a temporary work agency. As in Arulampalam et al. (2004) and Bassanini et al. (2007), and in line with human capital theory, we find that workers employed under fixed term contracts are less likely to invest in skill acquisition than workers with permanent contracts. For workers temporary employed through an external supplier – after all only 1% of all workers in our sample – no such effect exists, which we attribute to a lack of variation in our data. Finally, we also take up recent findings by Geishecker et al. (2012), who claim that offshoring to low-wage countries can explain about 28% of the increase in subjective job loss fears of German workers for the time span from 1995 to 2006. Adding an indicator variable, which takes a value of one whenever individuals stated that they face the fear of job loss and zero otherwise, we find that workers who reported subjective job loss fears are less likely to invest in on-the-job training. Together with the findings of Hummels et al. (2012), who show that workers who lose their job (through offshoring) are more likely to retrain their skills during the subsequent period of transitory unemployment, this result may hint at a delay of on-the-job training in favour of later out-of-job training measures, which are better tailored towards future re-employment possibilities. Important in our context is that none of these controls do significantly alter the average marginal effect of offshoring growth on individual skill upgrading. We now turn to Column (3) of Table 2, in which we include a binary variable that takes a value of one whenever new technologies, machines, or organizational features have been introduced at individual workplaces. There are two specific reasons why we have to control for the introduction of new technologies in our setting: On the one hand, our theoretical model from Section 2 reveals a close resemblance between the productivity effect of offshoring and sector biased technological change, which we have to tell apart if we want to identify the impact of offshoring growth on individual skill upgrading (cf. Feenstra and Hanson, 1999; Feenstra, 2010). On the other hand, it is likely that whenever new technologies are introduced this requires the (re-)training of involved workers, thereby mechanically leading to increased on-the-job training, which we do not want to confuse with our skill upgrading channel from Section 2. In line with these arguments, we find that workers who reported the introduction of new technologies at their workplace are more likely to participate in on-the-job training. Crucially, there still is a positive and highly significant link between offshoring growth and individual skill upgrading, although – as we would expect – with a lower estimate of the average marginal effect, which now stands at $\hat{\beta}^m = 0.1060$. A further concern relates to a possible co-movement of increased offshoring with the sectoral business cycle. If on-the-job training is pro-cyclical, for which – despite partly confounding results – at least some evidence exists (cf. Méndez and Sepúlveda, 2012), it could be the case that the positive association of individual skill upgrading with increased offshoring is nothing else than the reflection of the German business cycle, which from 2004 to 2006 was at the beginning of a boom period. To rule out this possibility, we include in Column (4) of Table 2 a control variable, which reflects workers' evaluation of the employing firms' current business success. In line with Méndez and Sepúlveda (2012), we find that workers employed by (very) successful firms tend to invest more often in on-the-job training. At the same time, the effect of offshoring growth on skill upgrading is almost unchanged. Admittedly, our measure for the business cycle is a simple one, focusing only on the employing firm, thereby ignoring possible inter-firm linkages in the respective industry. To come up with more comprehensive measure we also add the log-difference of real industry output in Column (5) of Table 2.[10] The effect of output growth on

[10]Including sectoral output growth might raise concern about possibly high multicollinearity between output

on-the-job training is insignificant, which is in line with the somewhat inconclusive literature on the cyclical properties of training (see Méndez and Sepúlveda, 2012; Bassanini et al., 2007). Not surprisingly, the effect of offshoring on skill upgrading is only slightly reduced and stays highly significant. Finally, in Column (6) of Table 2 we also control for the competition intensity within a given sector (cf. Görlitz and Stiebale, 2011). Given the positive correlation between firm size and offshoring activities, it could be the case that industries dominated by a few large firms have significantly different offshoring growth patterns than industries which are characterised by a competitive number of firms. At the same time skill upgrading – for several reasons – may also be linked to the intensity of competition within a sector: On the one hand increased competition could lead to higher training needs, necessary to secure a well trained workforce in a dynamic environment (Bassanini and Brunello, 2011). On the other hand, poaching, i.e. the transfer of general skills to a different employer via job switching, is usually found to be positively correlated with competition, which, hence, would lead to less training (Schmutzler and Gersbach, 2012). Controlling for industry level competition, we use the same measure as Görlitz and Stiebale (2011), the Herfindahl index of industry concentration.[11] We find a positive impact of competition on training, which is significant at the 1% level. Importantly, the effect of offshoring growth on individual skill upgrading is still significant, albeit slightly smaller in magnitude. Summing up, we find, that according to our preferred specification in Column (6) of Table 2 a doubling of the industry level offshoring intensity defined in Eq. (7) would increase the probability of on-the-job training participation by roughly 7.8 percentage points.

3.4 The timing of offshoring and on-the-job training

The "BIBB/BAuA Employment Survey 2005/06" took place from October 2005 and March 2006, and individuals where asked whether they participated in on-the-job training two years prior to the survey or since having the current job. We, thus, hold no precise information concerning the timing of individual training incidences. For our main analysis we therefore use a rather wide time frame covering offshoring growth from 2004 to 2006. As a robustness check, we now consider shorter and varying time frames, each covering the growth rate of offshoring on a year-to-year basis. Results are summarized in Table 3.

As we would expect, splitting up the time frame from 2004 to 2006 into two separate windows, covering 2004 to 2005 and 2005 to 2006, does not change our result: Increased offshoring still has a positive and significant impact on individual skill upgrading. Looking at a period (2002 -

growth and offshoring growth. However, this does not seem to be the case, as the coefficient on output growth stays insignificant even if offshoring growth is excluded from the regression.

[11] The Herfindahl index is published bi-annually by the German Monopoly Commission. We use the values for 2005.

Table 3: *Offshoring and on-the-job training: timing*

	(1)	(2)	(3)	(4)	(5)	(6)
Average marginal effect of:						
Offshoring growth 2002 - 2003	0.0178					
	(0.0121)					
Offshoring growth 2003 - 2004		-0.1589**				
		(0.0697)				
Offshoring growth 2004 - 2005			0.2672***			
			(0.0536)			
Offshoring growth 2005 - 2006				0.2216***		
				(0.0774)		
Offshoring growth 2006 - 2007					-0.1340***	
					(0.0476)	
Offshoring growth 2004 - 2006						0.1009***
						(0.0252)
Individual controls	yes	yes	yes	yes	yes	yes
Workplace and sectoral controls	yes	yes	yes	yes	yes	yes
KldB88 (2-digit) occupation FE	yes	yes	yes	yes	yes	yes
Pseudo R-squared	0.1335	0.1350	0.1370	0.1362	0.1354	0.1490
Observations	3,888	3,888	3,888	3,888	3,888	3,425

Notes: The table shows average marginal effect from estimating the variants of the Probit model in section 3.1 for different periods of offshoring growth. The dependent variable is a binary measure of observed skill upgrading through training in the two years prior to the survey or since having the current job. The Herfindahl index is not included since we do not have it for all respective time periods. Standard errors are cluster robust and are shown in parentheses below the coefficients. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

2003) that far precedes the time frame potentially covered by the survey we find – as expected – no effect. For the time frame from 2003 to 2004 we find a negative and significant coefficient. We interpret this finding as evidence, that on-the-job training is a lumpy investment, which individuals only use discontinuously over time with an optimal period of waiting between single training incidences. Thus, if increased offshoring between 2003 and 2004 caused more training in the period from 2003 to 2004 we would indeed expect that in the following period from 2004 to 2006 an immediate retraining becomes less likely for individuals who just completed their last training in the previous period. Interestingly, when focusing on future offshoring growth over the period from 2006 to 2007 we find a negative impact on the current training probability. Several explanations may account for this result. Assuming that individuals discount the costs and benefits of training at different rates, it could be the case that anticipated future offshoring growth leads to a postponement of contemporaneous training to later period when the benefits from training are even larger. Another explanation for the negative impact of future offshoring growth on contemporaneous training could be the lack of sufficient *long-run* controls capturing individual job loss fears. Given that offshoring tends to increase subjective job loss fears (cf. Geishecker et al., 2012), anticipated future offshoring growth could be associated with more uncertain long-run employment prospects, causing a reduction or delay of current on-the-job training. Finally, in Column (6) of Table 3 we only use individuals that are employed at the same employer since at least 2003. Because individuals where asked whether they participated in on-the-job training two years prior to the survey or since having the current job, this treatment gives us a more precise matching of the potential training period with the time frame for which we observe our offshoring variable. The resulting coefficient for sectoral offshoring growth is very similar to the one obtained from our preferred specification (Column (6) of Table 2) and highly significant.

3.5 Further robustness checks

In this subsection, we offer alternative specifications and check whether the link between offshoring growth and skill upgrading is driven by particular characteristics of our data set in terms of measurement or outliers. Detailed results can be found in Table 6 in the Appendix. At first, in Column (1) of Table 6 we look at the growth rate of worldwide offshoring, instead of the growth rate of non-OECD offshoring intensities. We do this to provide evidence for an alternative measure of offshoring. We find a positive and significant coefficient – which, somewhat surprisingly, is even larger than what we have estimated before. Secondly, in Column (2) we look at non-OECD offshoring again and include the growth rate of the export share in production to control for influences related to overall international exposure. In column (3) we use sample weights provided in the data and re-run our preferred specification using these weights. Note, however, that the data set is designed by the BIBB to be balanced and adjustments are taken to control for under representation of low-skilled individuals. Thus, it is not surprising to observe very similar coefficients, both in terms of significance and magnitude. Next, we drop in Column (4) four industries (tobacco; leather & luggage; office machinery & computers; coke & refined petroleum) in which results, due to a low number of observations, could easily be affected by outliers. In Column (5) we drop the two industries with the largest (other transport equipment) and smallest (coke & refined petroleum) change in non-OECD offshoring, again to rule out dependence on outliers, which could play an important role in our relatively small sample. Similarly, in Column (6) we drop the industries with the highest (chemicals) and lowest (textiles) average training participation rates. Reassuringly, all those changes have almost no effect on the coefficient of sectoral offshoring growth, which remains positive and significant throughout all specifications. Finally, let us recall our theoretical model from section 2, in which training participation is modeled as a worker's decision and it is the worker to whom both the cost and the benefits associated with individual skill upgrading accrue. Translating this mechanism one to one into our empirical model would require a distinction between employer-financed and self-financed on-the-job training. Unfortunately, this information is not available to us. However, we know whether a certain training measure can be traced back to the respective worker's own initiative or to some extrinsic motivation. Assuming that training which workers' started by own initiative is more likely to be also self-financed, we drop all cases in which workers' training participation followed from the order or suggestion of the respective employer. The results are shown in Column (7). Controlling for workers' initiative to start on-the-job training does not imply a correction of effect the growth rate of offshoring has on individual training participation. Importantly, the coefficient is still significant and of similar size when compared to the coefficient that results from the estimation of the full sample.

4 Conclusion

In this study we have derived a positive link between the offshoring of tasks and the individual propensity to invest in on-the-job training. In particular, we developed a theory that outlines a mechanism inducing employed individuals to select into training – a new aspect in the literature linking offshoring and training, which has so far mostly analysed training responses to worker displacement. In our model offshoring allows firms to save on costs when relocating parts of their production abroad. The resulting costs savings are handed through to domestic workers, whose wages are scaled up, thereby opening up so far unrealized skill upgrading possibilities. We test for this intuitive mechanism, using data from German manufacturing, and find that industry level offshoring growth rates indeed correlate with the individual probability of on-the-job training in a positive and highly significant way. In obtaining this effect, we explicitly control for a wide set of individual and workplace characteristics and in particular take into account technological change at the workplace and industry output growth as major determinants of individual on-the-job training.

References

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 4, pages 1043–1171. Elsevier, North Holland/NL. 6

Acemoglu, D., Gancia, G., and Zilibotti, F. (2012). Offshoring and Directed Technical Change. *NBER Working Paper*, (18595). 11

Acemoglu, D. and Pischke, J.-S. (1998). Why Do Firms Train? Theory And Evidence. *Quarterly Journal of Economics*, 113(1):78–118. 10

Antras, P. and Helpman, E. (2004). Global Sourcing. *Journal of Political Economy*, 112(3):552–580. 6

Arulampalam, W., Booth, A. L., and Bryan, M. L. (2004). Training in europe. *Journal of the European Economic Association*, 2(2-3):346–360. 3, 4, 13, 15

Bassanini, A., Booth, A., Brunello, G., De Paola, M., and Leuven, E. (2007). *Education and Training in Europe*, chapter Workplace Training in Europe, pages 143 – 309. Oxford University Press. 3, 4, 10, 12, 13, 14, 15, 17

Bassanini, A. and Brunello, G. (2011). Barriers to Entry, Deregulation and Workplace Training: A Theoretical Model with Evidence from Europe. *European Economic Review*, 55(8):1152–1176. 17

Baumgarten, D., Geishecker, I., and Görg, H. (2013). Offshoring, tasks, and the skill-wage pattern. *European Economic Review*, 61(0):132 – 152. 3, 4, 10, 11

Blinder, A. (2006). Offshoring: The Next Industrial Revolution? *Foreign Affairs*, 85(2):113–128. 14

Crinò, R. (2008). Offshoring, multinationals and labour market: A review of the empirical literature. *Journal of Economic Surveys*, 23(2):197–249. 4

Davies, R. and Desbordes, R. (2012). Greenfield FDI and Skill Upgrading. *CEPR Discussion Paper*, (8912). 4, 11

Dustmann, C. and Schönberg, U. (2012). What Makes Firm-based Vocational Training Schemes Successful? The Role of Commitment. *American Economic Journal: Applied Economics*, 4(2):36–61. 10

Ebenstein, A., Harrison, A., McMillan, M., and Phillips, S. (2013). Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys. *Review of Economics and Statistics*. forthcoming. 3, 4, 10, 11

Eurofound (2012). Fifth european working conditions survey. Publications Office of the European Union, Luxembourg. 2

Feenstra, R. (2010). *Offshoring in the Global Economy: Microeconomic Structure and Macroeconomic Implications*. The MIT Press. 3, 4, 16

Feenstra, R. and Hanson, G. (1996). *Political Economy of Trade Policies: Essays in Honor of Jagdish Bhagwati*, chapter Foreign Investment, Outsourcing and Relative Wages, pages 87–127. MIT Press, Cambridge. 3

Feenstra, R. and Hanson, G. (1999). The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979–1990. *Quarterly Journal of Economics*, 114(3):907–940. 3, 12, 16

Geishecker, I. and Görg, H. (2008). Winners and Losers: A Micro-Level Analysis of International Outsourcing and Wages. *Canadian Journal of Economics*, 41(1):243–270. 3, 10, 11, 12

Geishecker, I., Riedl, M., and Frijters, P. (2012). Offshoring and Job Loss Fears: An Econometric Analysis of Individual Perceptions. *Labour Economics*, 19(5):738 – 747. 11, 15, 18

Goos, M., Manning, A., and Salomons, A. (2009). Job Polarization in Europe. *American Economic Review P&P*, 99(2):58–63. 14

Görlitz, K. and Stiebale, J. (2011). The Impact of Product Market Competition on Employers Training Investments. Evidence from German Establishment Panel Data. *De Economist*, 159(1):1–23. 4, 11, 17

Grossman, G. and Rossi-Hansberg, E. (2008). Trading Tasks: A Simple Theory of Offshoring. *American Economic Review*, 98(5):1978–1997. 1, 2, 3, 4, 5, 6

Grossman, G. and Rossi-Hansberg, E. (2012). Task Trade Between Similar Countries. *Econometrica*, 80(2):593–629. 12

Hall, A. and Tiemann, M. (2006). BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2006, suf 1.0. Technical report, Research Data Center at BIBB (ed.); GESIS Cologne, Germany (data access); Federal Institute of Vocational Education and Training, Bonn. 10

Hummels, D., Jørgensen, R., Munch, J., and Xiang, C. (2013). The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data. *American Economic Review*, forthcoming. 2, 14

Hummels, D., Munch, J., Skipper, L., and Xiang, C. (2012). Offshoring, Transition, and Training: Evidence from Danish Matched Worker-Firm Data. *American Economic Review P&P*, 102(3):424–428. 2, 4, 8, 11, 16

Kohler, W. (2004). International Outsourcing and Factor Prices with Multistage Production. *Economic Journal*, 114(494):C166–C185. 2

Méndez, F. and Sepúlveda, F. (2012). The Cyclicality of Skill Acquisition: Evidence from Panel Data. *American Economic Journal: Macroeconomics*, 4(3):128–152. 4, 11, 12, 16, 17

Moser, C., Urban, D. M., and Weder di Mauro, B. (2009). Offshoring, Firm Performance and Establishment-Level Employment: Identifying Productivity and Downsizing Effects. *CEPR Discussion Paper*, (7455). 14

Ottaviano, G., Peri, G., and Wright, G. (2013). Immigration, Offshoring and American Jobs. *American Economic Review*, 103(5):1925–59. 14

Pischke, J. (2001). Continuous Training in Germany. *Journal of Population Economics*, 14(3):523–548. 14

Rodríguez-Clare, A. (2010). Offshoring in a ricardian world. *American Economic Journal: Macroeconomics*, 2(2):227–58. 2

Rohrbach, D. (2009). The BIBB/IAB-and BIBB/BAuA Surveys of the Working Population on Qualification and Working Conditions in Germany. Data and Methods Manual. Technical report. 10

Schmutzler, A. and Gersbach, H. (2012). Product Markets and Industry-Specific Training. *RAND Journal of Economics*, 43(3):475 – 491. 17

5 Theory appendix

Proof of proposition 1

Note that $\gamma = \Omega_S^\alpha \Omega_N^{1-\alpha} < 1$ in Eq. (1′) still endogenously depends on domestic factor prices, w_S and w_N, respectively. In order to obtain a testable prediction on how falling offshoring costs,

τ_S and τ_N, relate to the individual skill upgrading decision of domestic workers in Eq. (1′) we have to replace w_S and w_N in Ω_S and Ω_N. Using the definitions of $\Omega_S = (\tau_S w_S^*/w_S)^{1-\theta} \leq 1$ and $\Omega_N = (\tau_N w_N^*/w_N)^{1-\theta} \leq 1$, we replace w_S and w_N by Eqs. (2) and (3). Skill upgrading condition (1′) can then be written as

$$u = \frac{\alpha s^{\alpha-1} - (1-\alpha) s^{\alpha}}{\left[A (\tau_S w_S^*)^{\alpha} (\tau_N w_N^*)^{1-\alpha} \Omega_S^{\alpha} \Omega_N^{1-\alpha}\right]^{(1-\theta)}} - \kappa,$$

in which $A \equiv 1/[\alpha^{\alpha} (1-\alpha)^{1-\alpha}] > 0$ is a positive constant. Unfortunately the above expression still depends on $\gamma = \Omega_S^{\alpha}\Omega_N^{1-\alpha}$. However, replacing again w_S and w_N in Ω_S and Ω_N by Eqs. (2) and (3), we find that after K iterations Eq. (1′) can be rewritten as a sequence $Z(K)$ with

$$u \equiv Z(K) = \frac{\alpha s^{\alpha-1} - (1-\alpha) s^{\alpha}}{\left[A (\tau_S w_S^*)^{\alpha} (\tau_N w_N^*)^{1-\alpha}\right]^{\sum_{k=1}^{K}(1-\theta)^k} \left(\Omega_S^{\alpha}\Omega_N^{1-\alpha}\right)^{(1-\theta)^K}} - \kappa.$$

Letting K go to infinity we find that sequence $Z(K)$ converges to

$$\lim_{K\to\infty} Z(K) = \frac{\alpha s^{\alpha-1} - (1-\alpha) s^{\alpha}}{\left[A (\tau_S w_S^*)^{\alpha} (\tau_N w_N^*)^{1-\alpha}\right]^{\frac{1-\theta}{\theta}}} - \kappa,$$

as $\lim_{K\to\infty} \sum_{k=1}^{K} (1-\theta)^k = (1-\theta)/\theta$. The above equation no longer depends on w_S and w_N such that it is easy to infer that $\partial s/\partial \tau_S < 0$ and $\partial s/\partial \tau_N < 0$. Thus, a gradual decline in *any* offshoring cost, τ_S or τ_N, leads to more individual skill upgrading. Taking additionally into account that according to Eq. (4) the share of tasks performed domestically is proportional to the respective cost savings factor from offshoring, $\Omega_S \leq 1$ or $\Omega_N \leq 1$, proposition 1 follows immediately. *QED*

6 Empirical appendix

Data description and summary statistics

We source our data from the following providers: The data on (nominal) output at the industry level stem from the OECD's STAN database. Deflation of output for the calculation of the real growth rate control is done with industry specific producer price indices obtained from the German Statistical Office. Industry competition for 2005 is taken from the Monopoly Commission's annual report to the Federal German government and can be accessed at `http://www.monopolkommission.de/haupt.html`. The input output tables used in the calculation of the offshoring indices are part of the national accounts provided by the German Statistical Office at https://www.destatis.de/EN/Homepage.html. Data on industry level trade and output are taken from the OECD STAN data base, as are the export shares in production.

Table 4 summarizes all variables in our final sample of 3,917 individuals which are full-time employed in manufacturing. More than half (59%) of the respondents participated in on-the-job

Table 4: *Summary statistics: estimation sample*

Variables	share	mean	st. dev.
Individual characteristics			
On-the-job training	0.586	-	-
Thereof by own initiative	0.421	-	-
Age	-	42.06	10.06
16 - 29	0.117	-	-
30 - 39	0.297	-	-
40 - 49	0.345	-	-
50 - 64	0.231	-	-
$\geq$ 65	0.010	-	-
Education			
Low	0.677	-	-
Medium	0.109	-	-
High	0.214	-	-
Further individual characteristics			
Important to have a career	0.173	-	-
Fixed term contract	0.055	-	-
Temporary work	0.011	-	-
Job loss fear	0.103	-	-
Female	0.241	-	-
Tenure		13.66	9.621
Employer size (# of employees)			
1 - 9	0.109	-	-
10 - 49	0.183	-	-
50 - 249	0.246	-	-
250 - 499	0.132	-	-
$\geq$ 500	0.332	-	-
Further employer characteristics			
New technology introduced	0.896	-	-
Current firm success (very) good	0.805	-	-
Industry characteristics			
Offshoring growth 2004 - 2006	-	.325	0.393
Output growth 2004 - 2006	-	0.079	0.114
Herfindahl index (x 1,000) 2005	-	60.363	83.684
Number of observations	3,917		

training. Of those who participated, 42% did so by own initiative. We can group individuals into five age groups, with the average worker being of age 42 having 14 years of tenure. Unsurprisingly, the majority of workers (76%) in manufacturing are male. We classify workers according to their education as high-skilled (university degree), medium-skilled (degree from a technical school, e.g. the German "Meister") and low-skilled (all residual workers). The majority of workers (68%) are classified as low-skilled, less are high- (21%) or medium-skilled (11%). Of the respondents 17% stated that having a career is important for them. Only a small fraction of all workers held a fixed term contract (6%) or were just temporarily employed (1%). Among all workers 10 % answered that they face the fear of job loss. We classify employers according to the number of employees and distinguish between five groups: firms with 1 - 9, 10 - 49, 50 - 249, 250 - 499 and more than 500 employees. The majority of firms (90%) introduced new technologies during the sample period. Overall the employing firm's success was largely seen as good or very good; 81% of the respondents answered in this way. Industry output growth is the growth of real output, calculated as log-difference. The Herfindahl index of industry concentration is the sum of the squared market shares of all market participants in the respective 2-digit NACE 1.1 industry.

Table 5: *Summary statistics: offshoring*

j	Industry classification	O_j	$\widehat{O}_j$	j	Industry classification	O_j	$\widehat{O}_j$
35	Other transport equip.	0.82	152.65	22	Publishing, printing	0.047	26.68
34	Motor vehicles	0.37	95.47	30	Office, computing mach.	8.17	23.76
27	Basic metals	2.15	86.07	15	Food, beverages	0.54	22.88
33	Medical, optical, precision instr.	0.61	52.01	29	Machinery, equipment	1.71	20.63
28	Fabricated metal prod.	0.30	39.38	20	Wood, cork prod.	1.02	19.23
25	Rubber, plastic	0.16	34.81	26	Non-metallic mineral prod.	0.31	13.31
24	Chemicals	0.83	34.32	36	Furniture	3.20	10.49
16	Tobacco	0.11	31.67	17	Textiles	4.63	8.03
18	Wearing apparel	5.60	30.45	32	Radio, television, comm.	9.83	5.36
19	Leather, luggage	7.70	29.27	31	Electrical machinery	1.52	4.19
21	Paper	0.49	27.79	23	Coke, refined petroleum	0.456	-52.44

Notes: The offshoring intensity O_j (in percent) is calculated for 2004. Offshoring growth $\widehat{O}_j$ (in percent) is calculated over the time span from 2004 to 2006. Industries are ranked in decreasing order according to the magnitude of sectoral offshoring growth.

Industry level offshoring is calculated as described in Eq. (7). For the industries 15-16, 17-19, and 21-22 the OECD STAN bilateral trade data base only holds information on combined non-OECD trade flows. We hence use the same share of non-OECD imports in total imports for the individual industries within each of the three aggregates and multiply them with total STAN imports, for which we have industry specific data in all cases. Checking the robustness of this approach, we dropped the respective sectors and still found our results presented in section 3.3 to be similarly sized and statistically significant. Table 5 gives an overview of offshoring intensities across industries, both in levels and growth rates.

Table 6: *Offshoring and on-the-job training: robustness*

	(1) import pen.	(2) with exports	(3) weighted	(4) no small ind.	(5) no 35 and 32	(6) no 24 no 17	(7) own initiative
Average marginal effect of:							
Offshoring growth	0.2423***	0.0815***	0.0626***	0.0748***	0.0850***	0.0827***	0.0763***
	(0.0664)	(0.0214)	(0.0192)	(0.0245)	(0.0229)	(0.0191)	(0.0203)
Age 30 - 39	-0.0045	-0.0043	-0.0306	-0.0016	-0.0033	0.0058	0.0171
	(0.0196)	(0.0196)	(0.0235)	(0.0203)	(0.0205)	(0.0196)	(0.0287)
Age 40 - 49	-0.0505**	-0.0501**	-0.0599**	-0.0462*	-0.0475**	-0.0420*	-0.0091
	(0.0231)	(0.0233)	(0.0296)	(0.0241)	(0.0234)	(0.0236)	(0.0308)
Age 50 - 64	-0.1406***	-0.1380***	-0.1602***	-0.1376***	-0.1318***	-0.1346***	-0.0875**
	(0.0278)	(0.0282)	(0.0327)	(0.0288)	(0.0289)	(0.0296)	(0.0362)
Age 65+	-0.3362***	-0.3338***	-0.3759***	-0.3343***	-0.3394***	-0.3256***	-0.1713***
	(0.0573)	(0.0568)	(0.0618)	(0.0577)	(0.0620)	(0.0616)	(0.0558)
Female	-0.0678***	-0.0678***	-0.1032***	-0.0645***	-0.0687***	-0.0655***	-0.0468**
	(0.0190)	(0.0189)	(0.0198)	(0.0187)	(0.0205)	(0.0222)	(0.0194)
Married	-0.0103	-0.0104	-0.0068	-0.0129	-0.0114	-0.0012	-0.0092
	(0.0215)	(0.0214)	(0.0243)	(0.0214)	(0.0226)	(0.0242)	(0.0227)
Tenure	0.0028	0.0028	0.0040	0.0027	0.0029	0.0008	-0.0015
	(0.0040)	(0.0039)	(0.0042)	(0.0040)	(0.0042)	(0.0032)	(0.0051)
Tenure squared	-0.0000	-0.0000	-0.0000	-0.0000	-0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Medium-skill	0.0363	0.0346	0.0246	0.0343	0.0308	0.0221	0.1134***
	(0.0353)	(0.0344)	(0.0336)	(0.0351)	(0.0359)	(0.0353)	(0.0411)
High-skill	-0.0002	0.0026	-0.0295	-0.0026	0.0006	0.0178	0.0253
	(0.0213)	(0.0216)	(0.0249)	(0.0218)	(0.0234)	(0.0213)	(0.0242)
Importance to have a career	0.0655***	0.0633***	0.0632***	0.0613***	0.0601***	0.0568***	0.0808***
	(0.0208)	(0.0204)	(0.0235)	(0.0207)	(0.0209)	(0.0215)	(0.0203)
Firm size 10 - 49	-0.0167	-0.0181	-0.0029	-0.0239	-0.0148	-0.0192	-0.1247***
	(0.0212)	(0.0212)	(0.0245)	(0.0218)	(0.0212)	(0.0219)	(0.0360)
Firm size 50 - 249	0.0533***	0.0505***	0.0690***	0.0488***	0.0546***	0.0401***	-0.0561***
	(0.0168)	(0.0162)	(0.0259)	(0.0162)	(0.0155)	(0.0151)	(0.0217)
Firm size 250 - 499	0.1021***	0.0977***	0.0874**	0.0914***	0.1014***	0.1007***	-0.0260
	(0.0290)	(0.0277)	(0.0387)	(0.0289)	(0.0288)	(0.0304)	(0.0243)
Firm size 500+	0.1290***	0.1203***	0.1041**	0.1152***	0.1115***	0.1119***	0.0309
	(0.0234)	(0.0241)	(0.0464)	(0.0239)	(0.0233)	(0.0272)	(0.0351)
Fixed term contract	-0.0790**	-0.0794**	-0.0637	-0.0801**	-0.0788**	-0.0993***	-0.0985***
	(0.0342)	(0.0330)	(0.0456)	(0.0331)	(0.0343)	(0.0334)	(0.0331)
Temporary work	0.0392	0.0418	0.0506	0.0156	0.0680	0.0445	0.0375
	(0.0522)	(0.0527)	(0.0932)	(0.0574)	(0.0534)	(0.0545)	(0.0957)
Job loss fear	-0.0517**	-0.0511**	-0.0616**	-0.0525**	-0.0562***	-0.0481**	-0.0426
	(0.0215)	(0.0209)	(0.0299)	(0.0212)	(0.0208)	(0.0210)	(0.0327)
New technology introduced	0.1637***	0.1646***	0.1488***	0.1633***	0.1687***	0.1676***	0.1293***
	(0.0220)	(0.0215)	(0.0269)	(0.0218)	(0.0224)	(0.0221)	(0.0285)
Current firm success (very) good	0.0341*	0.0393**	0.0401	0.0396**	0.0446**	0.0405*	0.0471**
	(0.0203)	(0.0198)	(0.0246)	(0.0193)	(0.0204)	(0.0210)	(0.0188)
Herfindahl index	0.0010***	0.0007***	0.0008***	0.0007***	0.0006***	0.0005***	0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Growth in export share of prod.		0.1904					
		(0.1495)					
KldB88 (2-digit) occupation FE	yes	yes	yes	yes	yes	yes	yes
Pseudo R-squared	0.1397	0.1395	0.1383	0.1393	0.1393	0.1279	0.2207
Observations	3888	3888	3888	3,845	3,685	3,421	2,623

Notes: The table shows average marginal effects from estimating variants of the Probit model specified in section 3.1. The reference category for firm size is 1 - 9 employees. The industry output growth is compute for 2004 to 2006. The Herfindahl index, which is published bi-annually by the German Monopoly Commission refers to 2005. Individual controls are the same as in column (6) of Table 1. Industry level controls are as in Table 2. Export share in production is taken from the OECD STAN data base. Standard errors are clustered at the industry level and shown in parentheses below the coefficients. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.