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Trade, tasks, and training: The effect of offshoring on individual skill upgrading

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

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June 2014

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 a variant of the Grossman and Rossi-Hansberg (2008) model of offshoring. By scaling up worker's wages, offshoring in our model creates previously unexploited skill upgrading possibilities and, thus, leads to more on-the-job training. Using data from German manufacturing, we establish a causal link between the growth in industry-level offshoring and an increased on-the-job training propensity at the individual level.

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 database 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 temporarily) displaces some workers from their jobs. As shown by Hummels, Munch, Skipper, and Xiang (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 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, 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) wage differential exceeds the associated cost of skill upgrading.

Focusing on this training indifference condition, we translate our theoretical model into an empirically testable specification. In line with our theoretical results, we 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 relates to the sectoral import

[1] For example, in the sample of Hummels, Jørgensen, Munch, and Xiang (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.

of intermediate products, which is a widely used measure to proxy for industry-level offshoring in the empirical trade literature (cf. Feenstra and Hanson, 1996b,a; Hijzen, Görg, and Hine, 2005; Feenstra and Hanson, 1999; Geishecker and Görg, 2008, 2011; Baumgarten, Geishecker, and Görg, 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, hence, ruling out a reverse causality bias. 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, 2011; Baumgarten, Geishecker, and Görg, 2013; Ebenstein, Harrison, McMillan, and Phillips, 2013). With respect to possible omitted observable variables that could be correlated with both training and offshoring, we make use of the detailed information contained in our data set. 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 already have been identified as major determinants of individual skill-upgrading decisions in the empirical training literature (cf. Arulampalam, Booth, and Bryan, 2004; Bassanini, Booth, Brunello, De Paola, and Leuven, 2007). Of particular interest for our application is 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 technological change (cf. Feenstra, 2010). Moreover, to identify a causal link between offshoring and individual skill upgrading, we adopt the instrumental variable approach recently put forward in Autor, Dorn, and Hanson (2013), and Dauth, Findeisen, and Suedekum

(2014) and exploit the rise of China to the world's major offshoring destination (cf. Baldwin and Lopez-Gonzalez, 2013) as an *exogenous* shock to the aggregate offshoring supply.

Our findings are in line with 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 rate 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, based on our preferred specification without or with instrumental variables, respectively.

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, Booth, Brunello, De Paola, and Leuven (2007) for an overview). On the other hand, we also add to the empirical trade literature which focuses on the implications offshoring has for domestic labor markets (see Baumgarten, Geishecker, and Görg (2013); Becker, Ekholm, and Muendler (2013); Ebenstein, Harrison, McMillan, and Phillips (2013) for recent examples). The first strand of the literature usually focuses on combinations of product and/or labor market based explanations to pin down individual on-the-job training decisions in a closed-economy setting, ignoring the impact that globalization may have on individual training decisions.[2] The empirical

[2] Arulampalam, Booth, and Bryan (2004) and Bassanini, Booth, Brunello, De Paola, and Leuven (2007) control for a comprehensive range of individual-level indicators to explain the selection of workers into on-the-job training.

trade literature, on the contrary, is mainly 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. Feenstra and Hanson, 1996a; Hijzen, Görg, and Hine, 2005; Crinò, 2012; Feenstra, 2010; Davies and Desbordes, 2012; Foster-McGregor, Stehrer, and Vries, 2013).[3] In these studies, individual skills are usually considered as fixed, such that skill upgrading is measured only at the *extensive* margin through changes in the composition of workforces at the sector and/or firm-level, rather than at the *intensive* margin, taking into account workers' individual training decisions. A notable exception in the trade literature is the paper by Hummels, Munch, Skipper, and Xiang (2012), which shows 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.[4] We complement this research by focusing on the vast majority of workers staying with their jobs and argue, that these workers 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

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.

[3]The earlier literature is reviewed in Crinò (2008) and Feenstra (2010). More recently, Becker, Ekholm, and Muendler (2013) have documented that offshoring is not only associated with a shift towards more high-skilled employment as such, but also towards more employment in non-routine and interactive tasks. Similarly, Liu and Trefler (2011) highlight the importance of occupational choice for understanding how domestic labor markets absorb the consequences of increased offshoring.

[4]The need for additional training becomes immediately clear once taking into account that workers, who are displaced from their manufacturing jobs due to offshoring usually experience a discrete wage drop, which is higher if the replacement is associated with a subsequent switch between sectors and/or occupations (cf. Crinò, 2010; Ebenstein, Harrison, McMillan, and Phillips, 2013).

includes a description of the econometric set-up, the data used, and the results obtained. A final section concludes the paper.

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

The goal of this section is to develop an intuitive visualisation of the link between 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. As in Grossman and Rossi-Hansberg (2008), we distinguish between a small-open-economy setting (without relative price effects) and an integrated world economy (with relative price effects). In Section 2.1 we develop our baseline small-open-economy model and derive our main result. Section 2.2 then relaxes the small-open-economy assumption.

2.1 Offshoring and individual skill upgrading in a small-open economy

To start with, we focus on a single-sector economy producing a homogeneous, constant-returns-to-scale *numéraire* Y at a given world market price normalised to $P \stackrel{!}{=} 1$. The production process combines two task sets, $\widetilde{S}$ and $\widetilde{N}$, which enter production at constant cost shares of α and $1-\alpha$, respectively. 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 task 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 constant-return-to-scale 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 suf-

ficiently low, i.e. if $w_j \geq \tau_j w_j^* \ \forall \ j \in \{S, N\}$, with $\tau_j \geq 1$ denoting the usual iceberg-type offshoring cost and w_j^* 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 $\omega_j(w_j, \tau_j w_j^*) = \Omega_j w_j$, where $\Omega_j \equiv \omega_j(w_j, \tau_j w_j^*)/\omega_j(w_j, w_j) \leq 1 \ \forall \ j \in \{S, N\}$ is defined as the cost savings factor from relocating tasks S^* or N^* abroad (cf. Grossman and Rossi-Hansberg, 2008).[5] Intuitively, the cost savings $\Omega_j \leq 1$ are linked to the international wage differential $\tau_j w_j^*/w_j \leq 1$ (including the offshoring cost $\tau_j \geq 1$): if the international wage gap widens, the cost savings from offshoring increase.[6]

The unit cost for final output Y may be expressed as $c(\omega_S, \omega_N)$. Since both task-sets account for a constant share in total cost, the unit-cost function $c(\omega_S, \omega_N)$ is multiplicatively separable into $c(\Omega_S w_S, \Omega_N w_N) = \gamma(\Omega_S, \Omega_N) c(w_S, w_N)$, with $\gamma(\Omega_S, \Omega_N) \leq 1$ denoting the total cost savings factor from (partly) offshoring the two inputs $\widetilde{S}$ and $\widetilde{N}$.[7] Thus, the aggregate productivity effect of offshoring $1/\gamma(\Omega_S, \Omega_N) \geq 1$ resembles Hicks-neutral technological progress at the sector level.[8]

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

[5] Note that without loss of generality it is always possible to scale technologies, $\widetilde{S} = \widetilde{S}(S, S^*)$ and $\widetilde{N} = \widetilde{N}(N, N^*)$ such that $\omega_j(w_j, w_j) = w_j \ \forall \ j \in \{S, N\}$.

[6] Appendix A.1 provides a closed-form solution for $\Omega_j \leq 1$, and shows that the link between $\Omega_j \leq 1$ and $\tau_j w_j^*/w_j \leq 1$ holds for an arbitrarily chosen (constant) elasticity of substitution $\sigma \in [0, \infty)$ between offshorable and non-offshorable tasks.

[7] The multiplicative separability of the unit-cost function into $\gamma(\Omega_S, \Omega_N)$ and $c(w_S, w_N)$ is an immediate consequence of the assumed Cobb-Douglas production technology and resembles the findings of Krugman (2000) and Xu (2001). Krugman (2000) shows that in a closed economy with two sectors and Cobb-Douglas preferences sector-biased technological change has no effect on the allocation of resources and hence on relative factor prices. In exactly the same way the (induced) productivity effect of offshoring $1/\Omega_j \geq 1$, which in our setting is biased to task-set $j \in \{S, N\}$, has no independent effect on factor prices, given that the aggregate production function combines the task-sets $\widetilde{S}$ and $\widetilde{N}$ in a Cobb-Douglas fashion. A detailed overview of how factor prices are affected if the Cobb-Douglas assumption is violated is given by Xu (2001).

[8] In the notion of Grossman and Rossi-Hansberg (2008) this result implies that the "productivity effect" of offshoring, which (generally) boosts wages, *always* dominates the "labor supply effect", which benefits (hurts) the factor that is offshored less (more) intensively.

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:

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

thereby keeping in mind that in equilibrium $u = 0$ has to 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 in Eq. (1) with the zero profit condition $c\,(w_N, w_S) = 1/\gamma(\Omega_S, \Omega_N)$. As outlined above, $1/\gamma(\Omega_S, \Omega_N) \geq 1$ thereby represents the aggregate productivity effect of offshoring, being equal to one under autarky and larger than one in an equilibrium with offshoring.

Figure 1 illustrates the effect of offshoring on on-the-job training. Starting out from the autarky equilibrium in point A and holding the domestic skill intensity notionally fixed at $s = s^a$, offshoring causes a radial outward expansion of the unit-cost curve by factor $1/\gamma(\Omega_S, \Omega_N) > 1$, which results in the hypothetical equilibrium in point B.[9] 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

[9]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 normalisation 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.

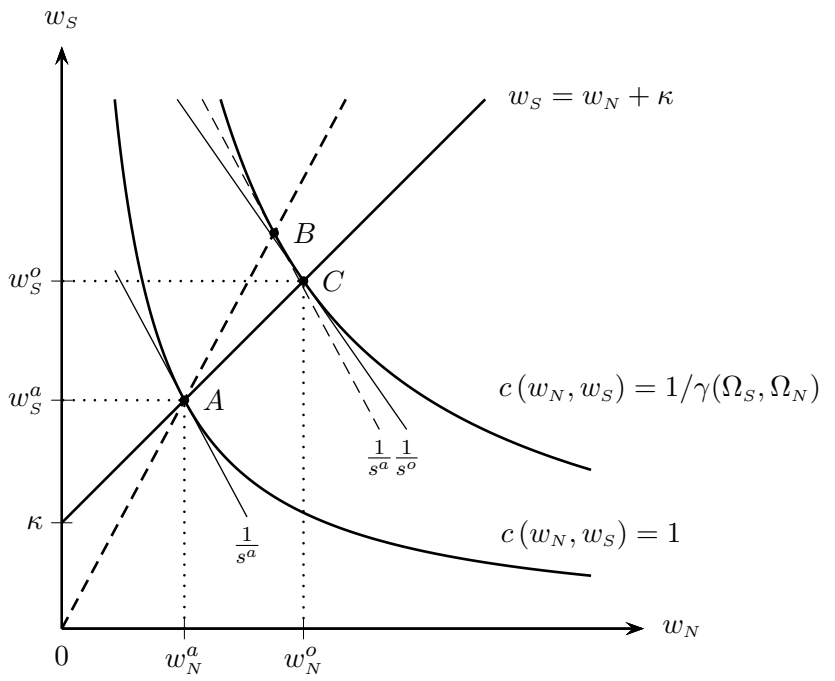

Figure 1: *Offshoring and individual skill upgrading in a small-open economy*

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 in point C is reached. This result is at the heart of our analysis and we frame it in the following Proposition:

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 A.2.[10]

Summing up, offshoring positively impacts the individual decision in favor of on-the-job

[10]Technically, by comparing two equilibria (with and without offshoring), Figure 1 links the productivity effect of offshoring (captured by $1/\Omega_j \geq 1 \ \forall \ j \in \{S, N\}$) to the domestic skill intensity s. However, the productivity terms $1/\Omega_j \ \forall \ j \in \{S, N\}$ thereby still depend on the domestic wages $w_j \ \forall \ j \in \{S, N\}$, which are endogenous to the model. Although it is immediately clear that induced feedback effects on domestic wages are of second order for firms' offshoring decisions, closed-form comparative statics for the link between falling offshoring cost τ_j and a higher domestic skill intensity s are provided for completeness in Appendix A.2.

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.[11] Also note that offshoring not only affects the skill upgrading decision of those individuals, which are directly hit by a (temporary) job loss through offshoring (cf. Hummels, Munch, Skipper, and Xiang, 2012). It is rather 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 a offshoring shock.

2.2 Offshoring and individual skill upgrading in an integrated world economy

As pointed out by Grossman and Rossi-Hansberg (2008), offshoring in an integrated world economy with two sectors has an additional relative price effect.[12] Since offshoring raises a sector's productivity through the access to cheap labor from abroad, the relative supply shifts towards the sector that offshores more intensively. To absorb the resulting excess supply, relative prices have to adjust, which – ceteris paribus – hurts the sector that offshores more intensively. The relative price effect thus partly offsets the productivity effect of offshoring, which in our setting implies that incentives for individual skill upgrading are reduced but *not* eliminated.

For illustration assume an integrated world economy with two regions (Home and Foreign). To capture the relative price effect addressed by Grossman and Rossi-Hansberg (2008), Home

[11] While this outcome is an immediate implication of the assumed Cobb-Douglas production technology (cf. Krugman, 2000), the task content of offshoring matters again for more general technologies. Thereby, two cases can be distinguished (cf. Xu, 2001). Provided the elasticity of substitution between the task sets is larger than one, an increase in $1/\Omega_S$ (an decrease in $1/\Omega_N$) would tend to decrease the domestic skill intensity, providing additional incentives for individual skill upgrading. On the contrary, if the elasticity of substitution between the task sets is smaller than one, an increase in $1/\Omega_S$ (an decrease in $1/\Omega_N$) would tend to increase the domestic skill intensity, thereby eroding further incentives for individual skill upgrading.

[12] The relative price effect of offshoring is prominently discussed in the literature. Among others see Samuelson (2004); Bhagwati, Panagariya, and Srinivasan (2004); Mankiw and Swagel (2006); Grossman and Rossi-Hansberg (2008) as well as Rodríguez-Clare (2010).

is assumed to produce a tradeable *numéraire* good Y, using intermediate inputs y_i produced in the sectors $i = 1$ and $i = 2$ at prices p_1 and p_2. As in the previous section sectoral output follows from a Cobb-Douglas production function, which combines the task sets $\widetilde{S}$ and $\widetilde{N}$. Foreign can produce the tradeable *numéraire* good Y on its own using a linear technology. However, it is assumed that this technology is sufficiently backward for workers in Foreign to specialize in the performance of offshored tasks instead. Tasks then – as before – are traded with Home against the *numèraire*.[13]

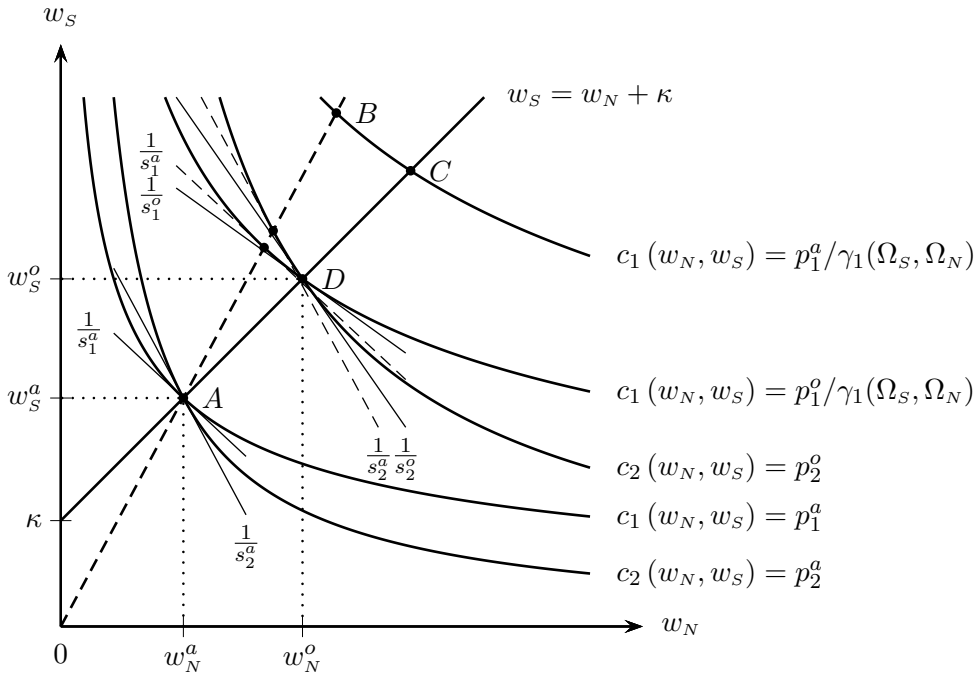

Figure 2: *Offshoring and individual skill upgrading in an integrated world economy*

Figure 2 focuses on the individual skill upgrading decision in Home. In the economy-wide equilibrium, workers at the same time have to be indifferent between skilled or unskilled employ-

[13] Mitra and Ranjan (2010) place their analysis in a similar setting, focusing on the impact of offshoring on unemployment in the presence of search frictions and imperfect inter-sectoral labor mobility, however.

ment *and* between employment in sector one or two. Under autarky (denoted by superscript a) this condition is met in point A, where *both* zero-profit conditions jointly intersect with the skill upgrading condition from Eq. (1). If offshoring becomes possible, for example in sector one, the corresponding zero-profit condition shifts out by factor $1/\gamma_1(\Omega_S, \Omega_N) \geq 1$. Holding domestic employment at the sector level notionally fixed, workers in sector one then would have an incentive to upgrade their skills, given that a notionally fixed skill intensity of $s = s_1^a$ in point B implies $u > 1$. However, when comparing wages across sectoral labor markets (point C vs. point A), it becomes clear that there also is a substantial inter-sectoral wage gap (for both tasks). Workers in sector two respond to this wage differential and switch to sector one. Along with this arbitrage, sector one (two) expands (contracts), which is reflected by a lower (higher) price $p_1^o < p_1^a$ ($p_2^o > p_2^a$) for input one (two) and a downward (upward) shift of sector one's (two's) zero-profit condition. The economy-wide equilibrium with offshoring (denoted by superscript o) finally is restored in point D, which features higher sectoral skill intensities $s_i^o > s_i^a \ \forall \ i = 1, 2$ than under autarky. Notably, the link between offshoring and individual skill upgrading thereby neither depends on the task- nor on the sector-bias of offshoring.

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.

3.1 Empirical strategy

As a natural starting point for an empirical implementation of Proposition 1, recall the training indifference condition in Eq. (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}, thus 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 (i.e. a change in our offshoring measure). 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.[14] 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:

$$Pr(U_{ij} = 1 \,|\, \cdot) = Pr(u_{ij} > 0 \,|\, \cdot), \tag{2}$$

[14] In our simple static framework, it is the change in offshoring and not the level that matters for skill upgrading. Without a change in offshoring that triggers a wage response, there are no incentives for skill upgrading, irrespective of the level of offshoring. In a more complex dynamic setting the level of offshoring of course may matter as well, since individuals will need to engage repeatedly in (re)training to maintain their skill level once it is reached. An empirical identification of such a level effect would require detailed knowledge concerning the frequency and timing of skill updating, which is beyond the scope of our contribution.

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. (2). We furthermore allow the individual training decision to depend on individual- and industry-specific characteristics, which we collect in the vectors $\mathbf{Y}_i$ and $\mathbf{X}_j$, respectively. While these vectors will be specified in more detail below, we may for now interpret them as additional controls capturing such things as (observable) 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. The probability of on-the-job training $Pr(U_{ij} = 1 \,|\, \cdot)$ in Eq. (2) can then be estimated by a Probit model based on the following empirical specification:

$$Pr\left(U_{ij} = 1 \,|\, \cdot\right) = Pr\left(u_{ij} > 0 \,|\, \cdot\right) = Pr(\beta_0 + \beta \widehat{O}_j + \mathbf{X}_j' \boldsymbol{\delta} + \mathbf{Y}_i' \boldsymbol{\eta} > \varepsilon_{ij} \,|\, \cdot). \tag{2'}$$

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 in Eq. (2′) 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 effects at the individual level (Geishecker and Görg, 2008; Ebenstein, Harrison, McMillan, and Phillips, 2013; Baumgarten, Geishecker, and Görg, 2013).

To limit the problem of omitted variables as another main reason for potentially biased estimates, we rely on a rich set of *observable* individual- and industry-specific covariates (summarized in the vectors $\mathbf{Y}_i$ and $\mathbf{X}_j$), which the training literature already has identified as important determinants of individual skill upgrading (cf. Bassanini, Booth, Brunello, De Paola, and Leuven, 2007). We introduce the respective controls in Section 3.2, before discussing their role against the background of our empirical results in Section 3.3.

Finally, there is the concern that our estimation results could also be biased due to *unobserved* heterogeneity at the industry-level. Ottaviano, Peri, and Wright (2013) provide an intuitive example for such unobserved heterogeneity in arguing that offshore workers compete with immigrant workers over the performance of tasks at the lower end and the middle of the complexity spectrum. Thus, if cheap immigrant workers for some reason would no longer be available in a given sector of the economy, this would cause domestic firms to rely on offshore workers instead. Depending on whether immigrant workers engage more or less frequently in on-the-job training than their domestic counterparts, more offshoring could be associated with more or less training, leading to a bias in our estimate. To obtain an unbiased estimate in the presence of such unobservable heterogeneity, we follow Autor, Dorn, and Hanson (2013) as well as Dauth, Findeisen, and Suedekum (2014) and exploit the opening of China's labor market as an exogenous shock to the aggregate offshoring supply, which then in Section 3.4 is used as an

instrument for our offshoring measure.

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 who participated between October 2005 and March 2006.[15] We use the 2005-2006 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: We set $U_{ij} = 1$ if a respondent stated that he/she participated in on-the-job training once or several times within the last two years or, alternatively, if a respondent is on the job for less than two years and if he/she participated in on-the-job training once or several times since being on his/her current job. Otherwise, we define $U_{ij} = 0$. After all, 59% of the workers in our sample participated in on-the-job training over the sample period. Being broadly defined, this variable has the advantage that it covers a wide array of training types and training durations, including short and informal training spells. Of course, the broad definition at the same time precludes a more refined analysis, taking the particularities of training types and training provision into account. In particular, the "BIBB/BAuA Employment Survey 2005/06" does not allow for a discrimination between self-financed and employer-financed training. However, we know that 42% of all training incidences resulted from workers' own initiatives. In a robustness

[15]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).

check we restrict our sample accordingly, arguing that skill upgrading, which was undertaken by own initiative, is more likely to be self-financed too. 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, Booth, Brunello, De Paola, and Leuven, 2007). In particular, we have information on demographic controls (age, gender, education) and workplace characteristics (firm size, tenure, employment contract).[16] In context of the recent offshoring literature (cf. Acemoglu, Gancia, and Zilibotti, 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. To control for business cycle effects, which have been linked to training by Méndez and Sepúlveda (2012), we directly rely on workers' assessment of the employing firm's current business success. Following Görlitz and Stiebale (2011), we also use Herfindahl indices of industry concentration from the German Monopoly Commission for 2005 to control for varying product market competition in different industries. Finally, R&D intensity and import penetration at the sector level are both computed from the OECD STAN database.

Offshoring is measured as a trade related phenomenon using data on imported intermediates.[17] In the spirit of Feenstra and Hanson (1999), we construct a *narrow* offshoring measure

[16]The "BIBB/BAuA Employment Survey 2005/06" is a representative survey of the German labor force, which – among other things – mirrors the firm-size distribution of manufacturing employment in Germany, as for example reported in Eurostat's Structural Business Statistics (SBS), available for 2008 as series `sbs_sc_sca_r2` at `http://epp.eurostat.ec.europa.eu/portal/page/portal/eurostat/home`.

[17]Proxies for offshoring based on foreign direct investment (FDI) often suffer from the insufficient decompos-

that is based on the sectoral use of imported intermediates, which originate from the *same* sector abroad. Thereby, two explicit refinements of the Feenstra and Hanson (1999) approach are considered in the construction of our offshoring variable. As pointed out by Geishecker and Görg (2008) and Baumgarten, Geishecker, and Görg (2013), the German input-output tables offer the *unique* possibility to differentiate directly between the use of domestic and imported intermediate inputs, which allows us to relax the "import comparability" assumption (cf. Houseman, Kurz, Lengermann, and Mandel, 2011, p. 113) from Feenstra and Hanson (1999).[18] Based on this information we compute the share λ_{jj^*} of sector j's imports that originate from the same sector j^* abroad and are used as intermediate inputs in the production of sector j. To obtain our offshoring measure

$$O_j = \frac{\lambda_{jj^*} IMP_j}{Y_j}, \tag{3}$$

we then multiply λ_{jj^*} with IMP_j, which is the total value of sector j's imports of goods, and finally divide by Y_j, which is the value of sector j's output. Again, we follow Geishecker and Görg (2008, 2011) and use sectoral output instead of the sector's total purchases of non-energy intermediates (cf. Feenstra and Hanson, 1999) as weight. The motivation behind this decision is to differentiate between domestic and international outsourcing. A trend towards domestic outsourcing would raise a sector's total purchases of non-energy intermediates, which according to the formula in Feenstra and Hanson (1999) mechanically lowers the sectoral offshoring share.

ability 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.

[18] For the U.S. only aggregate input-output tables exist. Feenstra and Hanson (1999) hence apply a proportionality assumption, according to which each industry's import share for a certain good is the same as the economy-wide import share for this good. In Feenstra and Jensen (2012) this assumption is relaxed. Furthermore, it is shown that there is a correlation of 0.68 between the offshoring shares obtained with and without the proportionality assumption.

If sector j's output (which additionally includes value added and energy purchases) is used in the denominator of Eq. (3), a rise in a sector's total purchases of non-energy intermediates through domestic outsourcing is (partly) offset by a decline in value added.

In our preferred specification we focus only on imported intermediates, which originate from non-OECD countries.[19] This choice has two reasons: On the one hand, we believe that the import of intermediates from low-income countries closely reflects the immediate cost-savings motive behind the offshoring decisions in our theoretical model from Section 2.[20] On the other hand, the emergence of China as the world's leading low-cost offshoring location (cf. Baldwin and Lopez-Gonzalez, 2013) can quite naturally be used as an *exogenous* shock to the offshoring supply from non-OECD countries, which we exploit in Section 3.4 along the lines of Autor, Dorn, and Hanson (2013) and Dauth, Findeisen, and Suedekum (2014). Nevertheless, to ensure comparability with established offshoring measures (cf. Feenstra and Hanson, 1999), we also consider world-wide offshoring in an alternative specification.

After all, this gives us a measure of offshoring that varies across 22 manufacturing industries (according to the NACE 1.1 classification). We use this information to compute the sectoral

[19] Our focus on non-OECD countries may raise concerns, whether the share λ_{jj^*} of inputs imported from these countries actually equals the share of inputs imported from *all* countries, as reported in the German IO-tables. Although, our data cannot explicitly answer this question, we do not believe that our results are driven by this proportionality assumption. Our confidence rests on the fact that all time-invariant weights should drop out in the construction of the offshoring growth rate $\hat{O}_j \equiv \Delta O_j / O_j$. Given the very short time span from 2004 to 2006 covered by our sample, it seems indeed unlikely that the input coefficients λ_{jj^*} in Eq. (3) have changed dramatically. Comparing the λ_{jj^*}s for 2004 with their counterparts in 2006 reveals the following picture: the mean λ_{jj^*} in 2004 was 0.1603, the mean change relative to 2006 was -0.0009.

[20] The theoretical trade literature has identified several alternative explanations for offshoring between similar high-income countries. Grossman and Rossi-Hansberg (2012) model trade in tasks between similar countries in an environment, in which firms have incentives to cluster the task production at the *same* location in order to exploit external scale economies at the country level. Amiti and Davis (2012) and Kasahara and Lapham (2013) extend Melitz (2003) and develop a model, in which heterogeneous firms import foreign intermediates from similar countries. Sourcing decisions thereby are driven by external increasing returns to scale in the assembly of intermediate goods (cf. Ethier, 1982) and do not follow from an immediate cost-savings motive. In fact, the variable unit cost for imported intermediates (including variable trade cost) in these models usually exceeds the variable unit cost of domestically produced intermediates.

growth rate of (non-OECD) 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 B). 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, non-OECD offshoring increased by 33% over the period from 2004 through 2006. To obtain our final estimation sample, we match the growth rate of our industry level 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 Baseline 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, Booth, Brunello, De Paola, and Leuven, 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. (3) would lead to an increase in the probability of on-the-job training participation by 0.1732. Taking into account

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***
	(.0534)	(.0515)	(.0490)	(.0423)	(.0415)	(.0246)
Age 30 - 39		0.0351	0.0331	−0.0161	−0.0087	−0.0130
		(.0228)	(.0234)	(.0254)	(.0232)	(.0199)
Age 40 - 49		−0.0142	−0.0132	−0.0855***	−0.0722**	−0.0691***
		(.0280)	(.0301)	(.0290)	(.0282)	(.0242)
Age 50 - 64		−0.0964***	−0.0946***	−0.1970***	−0.1811***	−0.1725***
		(.0330)	(.0320)	(.0280)	(.0279)	(.0247)
Age 65+		−0.3249***	−0.3257***	−0.4391***	−0.4214***	−0.4177***
		(.0774)	(.0788)	(.0676)	(.0665)	(.0555)
Female			−0.0630***	−0.0419**	−0.0393**	−0.0782***
			(.0232)	(.0200)	(.0198)	(.0176)
Married			−0.0100	−0.0148	−0.0147	−0.0112
			(.0238)	(.0235)	(.0233)	(.0226)
Tenure				0.0076**	0.0084**	0.0090**
				(.0038)	(.0039)	(.0039)
Tenure squared				−0.0001	−0.0001	−0.0001
				(.0001)	(0.0001)	(0.0001)
Medium-skill				0.1181***	0.1169***	0.0383
				(.0372)	(.0368)	(.0350)
High-skill				0.2118***	0.2117***	0.0169
				(.0255)	(.0258)	(.0204)
Importance to have a career					0.0628***	0.0651***
					(.0199)	(.0199)
KldB88 (2-digit) occupation FE:	no	no	no	no	no	yes
Pseudo R-squared:	.0100	.0199	.0221	.0492	.0509	.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 16 - 29 years. 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.

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, Booth, Brunello, De Paola, and Leuven (2007) and Méndez and Sepúlveda (2012), we find the usual life-cycle pattern in

the results from Column (2), according to which older individuals are less likely to undertake on-the-job training than their younger 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 first sight contrasts with the findings of Arulampalam, Booth, and Bryan (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, Booth, Brunello, De Paola, and Leuven (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.[21] 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 (cf. Bassanini, Booth, Brunello, De Paola, and Leuven, 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, Booth, Brunello, De Paola, and Leuven, 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

[21] This high share of male employees is not a distinct feature of our sample. According to the EU Labor Force Survey for 2006, 71.2% of all workers employed in German manufacturing are male.

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.[22] 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 likely 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, Manning, and Salomons, 2009; Ottaviano, Peri, and Wright, 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 keep our individual controls from Column (6) in Table 1 throughout, while gradually adding additional workplace- and industry-level control

[22] 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.

variables in Table 2.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average marginal effect of:							
Offshoring growth	0.1110***	0.1120***	0.1073***	0.1092***	0.0796***	0.0771***	0.0735***
	(.0253)	(.0247)	(.0248)	(.0255)	(.0201)	(.0255)	(.0194)
Firm size 10 - 49	−0.0036	0.0003	−0.0138	−0.0195	−0.0192	−0.0193	−0.0204
	(.0225)	(.0216)	(.0216)	(.0216)	(.0213)	(.0212)	(.0211)
Firm size 50 - 249	0.0701***	0.0766***	0.0546***	0.0482***	0.0489***	0.0488***	0.0484***
	(.0170)	(.0152)	(.0164)	(.0165)	(.0162)	(.0162)	(.0161)
Firm size 250 - 499	0.1241***	0.1315***	0.1062***	0.0982***	0.0964***	0.0965***	0.0954***
	(.0303)	(.0292)	(.0281)	(.0273)	(.0282)	(.0283)	(.0290)
Firm size 500+	0.1518***	0.1580***	0.1340***	0.1255***	0.1172***	0.1169***	0.1148***
	(.0284)	(.0270)	(.0263)	(.0248)	(.0239)	(.0240)	(.0236)
Fixed term contract		−0.1047***	−0.0876***	−0.0878***	−0.0905***	−0.0901***	−0.0886***
		(.0329)	(.0323)	(.0321)	(.0330)	(.0332)	(.0338)
Temporary work		0.0225	0.0505	0.0465	0.0350	0.0347	0.0375
		(.0552)	(.0543)	(.0534)	(.0548)	(.0546)	(.0533)
New technology introduced			0.1728***	0.1705***	0.1689***	0.1687***	0.1681***
			(.0230)	(.0229)	(.0227)	(.0227)	(.0232)
Current firm success (very) good				0.0540***	0.0524***	0.0525***	0.0465**
				(.0203)	(.0194)	(.0194)	(.0198)
Industry Herfindahl index					0.0006***	0.0006***	0.0007***
					(.0001)	(.0001)	(.0001)
Industry R&D intensity						0.0012	0.0074**
						(.0041)	(.0034)
Industry growth in import penetration ratio							0.5467***
							(.0997)
Individual controls:	yes	yes	yes	yes	yes	yes	yes
KldB88 (2-digit) occupation FE:	yes	yes	yes	yes	yes	yes	yes
Pseudo R-squared:	.1240	.1258	.1346	.1362	.1384	.1384	.1413
Observations:	3888	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 Herfindahl index, which is published bi-annually by the German Monopoly Commission refers to 2005. Research and development intensity and import penetration ratio are taken from the OECD STAN database. 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.

We start with the inclusion of firm size controls in Column (1) of Table 2. In line with Bassanini, Booth, Brunello, De Paola, and Leuven (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, Urban, and Weder di Mauro, 2009; Hummels, Jørgensen, Munch, and Xiang, 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 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, Booth, and Bryan (2004) and Bassanini, Booth, Brunello, De Paola, and Leuven (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. 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 workplaces 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 given a possible link between offshoring and technology upgrading – with a lower estimate of the average marginal effect, which now stands at $\hat{\beta}^m = 0.1073$. 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. [23]

Finally, in Column (5) 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 characterized 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

[23] 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 a more comprehensive measure we also added the log-difference of real industry output. However, since the inclusion of sectoral output growth has no independent effect on on-the-job training, leaving at the same time the coefficient of our firm-success variable unchanged, we decided to drop sectoral output growth, which by construction is correlated with our offshoring measure.

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). To control for competition at the industry level, we use the same measure as Görlitz and Stiebale (2011), the Herfindahl index of industry concentration.[24] 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. To validate our previous results, we include in Column (6) the industry-level R&D intensity as a broader measure for sector level technological change. Given that our preferred technology variable introduced in Column (3), relates to individual workplaces, the industry-level R&D intensity may be more appropriate to capture sector-level trends in technological change. Interestingly, a higher R&D intensity only has the expected positive effect (cf. Bassanini, Booth, Brunello, De Paola, and Leuven, 2007) when simultaneously controlling in Column (7) for changes in import penetration at the industry level. The latter variable thereby is included to capture more general trade developments beyond trade in intermediate goods. Importantly, our offshoring measure is only marginally reduced in both specifications. Summing up, we find that, according to our preferred specification in Column (7) of Table 2, a doubling of the industry level offshoring intensity defined in Eq. (3) is associated with an increase in the probability of on-the-job training participation by 0.0735.

In the Appendix we conduct several robustness checks to verify the results from our preferred

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

specification in Column (7) of Table 2. In Column (1) of Table 6 we look at the growth rate of worldwide offshoring instead of the growth rate of non-OECD offshoring, with the former variable still positively affecting individual training propensities.[25] To address the concern that in empirical settings with a small number of clusters (22 industries in our case) inference on cluster-robust standard errors may be invalid (cf. Cameron and Miller, 2014), we rerun our preferred specification in Column (7) of Table 2 as a linear probability model and conduct inference based on the wild bootstrap-t procedure of Cameron, Gelbach, and Miller (2008).[26] Column (2) of Table 6 in the Appendix reports the coefficients from the linear probability model together with the corresponding p-values from the bootstrap procedure. The obtained coefficients are highly significant and of comparable size as in our preferred Probit specification. In Column (3) of Table 6 we use sample weights provided in the data and obtain similar results, both in terms of significance and magnitude.[27] Finally, we drop all observations in which workers' training participation cannot be traced back to the respective worker's own initiative.

[25]Unlike the growth in non-OECD offshoring, the growth in worldwide offshoring by construction is highly correlated with import penetration growth at the sector level. We hence excluded import penetration growth from the set of controls, which may also explain, why the average marginal effect of offshoring growth becomes larger.

[26]The wild cluster bootstrap-t procedure developed by Cameron, Gelbach, and Miller (2008) is tailor fit to linear models. Kline and Santos (2012) suggest a score based bootstrap procedure for non-linear applications. Yet, this procedure requires an equal number of observations within clusters, which is not the case in our setting. Since, to the best of our knowledge, so far there exists no approach that implements an asymptotic refinement for our non-linear model without a constant number of observations across clusters, we cannot directly test the robustness of our preferred specification in this regard. Nevertheless, to address the issue, we re-estimate our preferred specification from Column (7) in Table 2 as a linear probability model and conduct inference based on the wild bootstrap-t procedure of Cameron, Gelbach, and Miller (2008). Specifically, we use the post estimation program `bootwildct` provided by Bansi Malde, which imposes the null hypothesis and uses Rademacher weights in the bootstrap procedure. This program is available under `http://www.ifs.org.uk/publications/6231`.

[27]Column (4) in Table 6 drops 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. 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.

Assuming that training which workers started by own initiative is more likely to be also self-financed, we obtain a proxy for self-financed on-the-job training, which more accurately mirrors our theoretical model from section 2. Results are reported in Column (7) of Table 6 and of similar size when compared to the coefficients obtained from the estimation of the full sample.

3.4 Instrumental variables

The analysis in Section 3.3 links the growth rate of offshoring to the probability of individual skill upgrading under the assumption that changes in our offshoring measure indeed represent a source of exogenous variation. A possible threat to our identification strategy hence exists in form of *unobservable* industry-level shocks, which may simultaneously affect sectoral offshoring growth *and* individual training decisions. To address this problem, we develop an instrument in the spirit of Hummels, Jørgensen, Munch, and Xiang (2013), Autor, Dorn, and Hanson (2013), and Dauth, Findeisen, and Suedekum (2014), which is correlated with sectoral offshoring growth but uncorrelated with individual training incidences. In particular, we exploit the fact that the emergence of China as a major destination country for offshoring not only represents a positive supply shock to Germany but also to *all* other high-income countries which seek to import intermediate inputs from low-cost locations abroad. Hence, using the sectoral growth rate of the output share of Chinese intermediates imported by high-income countries *other* than Germany as an instrument for the German industry-level offshoring growth purges the impact of unobservable heterogeneity at the sector-level and identifies the causal effect of sectoral offshoring growth on individual on-the-job training decisions.

As summarized in Dauth, Findeisen, and Suedekum (2014) three conditions have to hold for

our instrument to be valid: First, the instrument should have explanatory power to avoid a weak-instrument problem. Second, unobserved general supply and demand shocks in the instrument group should not be too strongly correlated with these unobservable shocks in Germany, since otherwise the instrument might simply pick up this correlation. Finally, to ensure that the exclusion restriction is not violated, offshoring from countries in our instrument group to China should not have an independent effect on German industries other than the one implied through the exogenous emergence of China as the world's factory for intermediate inputs.

Striking evidence for rise of China as a major supplier of intermediate inputs can be found in Baldwin and Lopez-Gonzalez (2013). Exploiting the recently compiled World-Input-Output Database (WIOD), they document that supply-chain trade between 1995 and 2009 has experienced a tremendous shift towards Asia, with China as the only big gainer on the sales side. Importantly, as argued by Autor, Dorn, and Hanson (2013) this pattern most likely is a result of China's own rapid productivity growth (reinforced by China's accession to the WTO in 2001), rather than the outcome of poor productivity growth in other world regions as the EU.[28] Accordingly, in our first stage regression below we find a strongly positive and significant relationship between the sectoral growth in the output share of intermediates imported by countries in our instrument group and the respective industry-level offshoring growth in Germany.

Whether the conditions two and three are likely to hold crucially depends on the appropriate choice of countries belonging to our instrument group. Following the reasoning in Dauth, Findeisen, and Suedekum (2014), we focus on similar high-income countries as Germany, excluding,

[28] China's accession to the WTO in 2001 lead to a major acceleration in the growth of Chinese exports (of intermediates). According to OECD STAN data, exports grew over the relevant sample period from 2004 to 2006 by 69%, which is more than a growth of 65% from 2001 to 2003, and in line with evidence on lagged effects of trade liberalization as in Baier and Bergstrand (2007).

however, all direct neighbors as well as other members of the European Monetary Union. For the first set of countries (such as France or Austria) unobserved industry-level shocks presumably are highly correlated with those in Germany, representing an obvious obstacle to our identification strategy. For the second country set strong ties with Germany exist through a common currency, which prevents the alignment of exchange rates among members of the currency union, such that offshoring to China in these countries could have an independent effect on German industries, violating our exclusion restriction. Based on the same reasoning the US is excluded, taking into account the US economy's predominant role in the world economy. Our final instrument group hence resembles the one defined for Germany by Dauth, Findeisen, and Suedekum (2014) and comprises Canada, Japan, South Korea, Sweden and the United Kingdom.[29] The share of imported Chinese intermediates in these countries can then be computed consistently for all counties using the OECD STAN Bilateral Trade by end-use database.

Column (1) of Table 3 presents the outcome of our instrumental variable estimation. Most importantly, the estimated effect of non-OECD offshoring growth on observed training participation is still positive and highly significant. The first stage result shows a positive and significant relation between (relative) changes in the output share of imported intermediates within the instrument group and German industry-level offshoring growth. Despite having a valid instrument, a Wald test does not reject the exogeneity of our initial offshoring variable. Following Geishecker and Görg (2011), we hence conclude that the efficiency loss associated with instrumenting offshoring is not justified and that our estimates reported in Table 2 represent

[29] In the choice of our instrument group we are somewhat limited through data availability issues, in particular with respect to industry-level output values. Relative to Dauth, Findeisen, and Suedekum (2014), we hence exclude Australia, New Zealand, and Norway. Instead of Singapore we add South Korea to our instrument group. We emphasize that our results are robust to the composition of the final instrument group. Excluding any one of the countries of our final instrument group always yields similar results to the ones we report below.

Table 3: *Offshoring and on-the-job training: Instrumental Variable Regression*

Average marginal effect of:	
Offshoring growth	0.1694**
	(.0748)
First stage coefficient	0.7723*
	(.3170)
Wald test of exogeneity:	
$\chi^2(1)$	1.68
p-value	0.1949
Individual-level controls:	yes
Industry-level controls:	yes
Observations:	3,888

Notes: The table shows the average marginal effect of the industry-level growth rate of offshoring on the probability of observing positive training incidence. The growth rate of offshoring is instrumented using the growth rate of imported intermediate inputs (scaled by output) from China for the IV-group of countries (CAN, JPN, SWE, GBR, KOR). The model includes all controls included in our preferred specification in Column (7) of Table 2. 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.

consistent estimates of the model parameters.[30]

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 analyzed training responses to worker displacement. In our model, offshoring allows firms to save on costs when relocating parts of their production abroad. The resulting cost savings are handed through to domestic workers whose wages are scaled up, thereby opening up so far unrealized skill upgrading possibilities.

[30]We also checked, whether China's exogenous rise can be used as an instrument for worldwide offshoring growth. Thereby it turned out that China's remarkable rise – although sufficiently strong to be significantly correlated with the offshoring supply from other non-OECD countries – delivers only a weak instrument, when considered as an exogenous shock to the worldwide offshoring supply.

We test for this intuitive mechanism using data from German manufacturing and find that the industry level growth rate of offshoring to non-OECD countries is strongly and robustly linked with the individual probability of on-the-job training. In obtaining this effect, we explicitly control for a wide set of individual, workplace and industry characteristics. In addition, we employ an instrumental variable strategy which confirms our results and suggest a causal nature of the relation between the growth of non-OECD offshoring and on-the-job training.

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A Theory appendix

A.1 The cost savings from offshoring

Let

$$\widetilde{S}\left(S,S^{*}\right)=B\left[\theta S^{\frac{\sigma-1}{\sigma}}+\left(1-\theta\right)\left(S^{*}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{A.1}$$

$$\widetilde{N}\left(N,N^{*}\right)=B\left[\theta N^{\frac{\sigma-1}{\sigma}}+\left(1-\theta\right)\left(N^{*}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{A.2}$$

with $\theta\in(0,1)$, $\sigma\in[0,\infty)$ and $B\equiv\left[\theta^{\sigma}+(1-\theta)^{\sigma}\right]^{\frac{1}{\sigma-1}}>0\ \forall\ j\in\{S,N\}$. The unit cost for task set $j\in\{S,N\}$ can then be written as:

$$\omega_{j}(w_{j},\tau_{j}w_{j}^{*})=w_{j}\Omega_{j}\quad\text{with}\quad\Omega_{j}\equiv B\left[\theta^{\sigma}+(1-\theta)^{\sigma}\left(\frac{\tau_{j}w_{j}^{*}}{w_{j}}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}\quad\forall\ j\in\{S,N\}\,. \tag{A.3}$$

From inspection of Eq. (A.3) it follows that $\Omega_{j}=1$ if $w_{j}=\tau_{j}w_{j}^{*}$ and $\Omega_{j}<1$ if $w_{j}>\tau_{j}w_{j}^{*}$ for all $j\in\{S,N\}$. *QED*

A.2 Proof of Proposition 1

We follow Antras and Helpman (2004) as well as Acemoglu and Autor (2011) and assume the technology, according to which tasks are bundled together, to be Cobb-Douglas, such that $\widetilde{S}(S,S^*) = BS^{\theta}(S^*)^{1-\theta}$ and $\widetilde{N}(N,N^*) = BN^{\theta}(N^*)^{1-\theta}$, 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. Cost savings at the task-level then are given by $\Omega_j = (\tau_j w_j^*/w_j)^{1-\theta} \leq 1 \ \forall \ j \in \{S,N\}$ and proportional to the respective international wage differential (including the transport costs $\tau_j \ \forall \ j \in \{S,N\}$). Expressing the profit maximization problem of an offshoring firm as:

$$\pi = \max_{\widetilde{S},\widetilde{N}} \ \widetilde{S}^{\alpha}\widetilde{N}^{1-\alpha} - \Omega_S w_S \widetilde{S} - \Omega_N w_N \widetilde{N}, \tag{A.4}$$

the corresponding first order conditions can be derived as:

$$w_S(\tilde{s}) = \alpha \tilde{s}^{\alpha-1}/\Omega_S, \tag{A.5}$$

$$w_N(\tilde{s}) = (1-\alpha)\tilde{s}^{\alpha}/\Omega_N, \tag{A.6}$$

with $\tilde{s} \equiv \widetilde{S}/\widetilde{N}$ measuring the *overall* skill intensity in the entire production process (including domestic tasks, S and N, as well as foreign tasks, S^* and N^*). To uncover the link between the overall skill intensity $\tilde{s}$ and the domestic skill intensity s, Shephard's Lemma can be applied to $\omega_j(w_j, \tau_j w_j^*) = w_j \Omega_j \ \forall \ j \in \{S,N\}$, resulting in:

$$\frac{\partial \omega_S(w_S, \tau_S w_S^*)}{\partial w_S} \equiv \frac{S}{\widetilde{S}} = \theta\Omega_S \qquad \text{and} \qquad \frac{\partial \omega_N(w_N, \tau_N w_N^*)}{\partial w_N} \equiv \frac{N}{\widetilde{N}} = \theta\Omega_N. \tag{A.7}$$

Dividing both expressions in Eq. (A.7) by each other reveals how $\tilde{s}$ and s are linked:

$$\tilde{s} = \frac{\Omega_N}{\Omega_S} s. \tag{A.8}$$

Intuitively, under autarky (with $\Omega_j = 1 \ \forall \ j \in \{S, N\}$) 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 (i.e. $\tilde{s} \gtrless s$ if $N/\widetilde{N} \gtrless S/\widetilde{S}$).

Replacing $\tilde{s}$ in Eqs. (A.5) and (A.6) by Eq. (A.8) before substituting both wages into the training indifference condition (1), finally yields:

$$u = w_S(s) - w_N(s) - \kappa = \frac{\alpha s^{\alpha-1} - (1-\alpha) s^{\alpha}}{\Omega_S^{\alpha} \Omega_N^{1-\alpha}} - \kappa, \tag{A.9}$$

in which $\Omega_S^{\alpha} \Omega_N^{1-\alpha} < 1$ implies $s^o > s^a$. However, $\Omega_S^{\alpha} \Omega_N^{1-\alpha} < 1$ in Eq. (A.9) still endogenously depends on domestic factor prices $w_j \ \forall \ j \in \{S, N\}$. To obtain a testable prediction on how falling offshoring costs $\tau_j \ \forall \ j \in \{S, N\}$ relate to the individual skill upgrading decision of domestic workers in Eq. (A.9) $w_j \ \forall \ j \in \{S, N\}$ in $\Omega_j \ \forall \ j \in \{S, N\}$ has to be replaced. Using the definition of $\Omega_j = (\tau_j w_j^* / w_j)^{1-\theta} \leq 1 \ \forall \ j \in \{S, N\}$, we replace $w_j \ \forall \ j \in \{S, N\}$ by Eq. (A.5) or (A.6), respectively. Skill upgrading condition (A.9) then can be written as:

$$u = \frac{\alpha s^{\alpha-1} - (1-\alpha) s^{\alpha}}{\left[A \left(\tau_S w_S^*\right)^{\alpha} \left(\tau_N w_N^*\right)^{1-\alpha} \Omega_S^{\alpha} \Omega_N^{1-\alpha} \right]^{(1-\theta)}} - \kappa, \tag{A.10}$$

in which $A \equiv 1/[\alpha^{\alpha} (1-\alpha)^{1-\alpha}] > 0$ is a positive constant. Unfortunately, the above expression still depends on $\Omega_S^{\alpha} \Omega_N^{1-\alpha} < 1$. However, replacing again $w_j \ \forall \ j \in \{S, N\}$ in $\Omega_j \ \forall \ j \in \{S, N\}$

by Eq. (A.5) or (A.6), we find that after K iterations Eq. (A.9) can be rewritten as a sequence $Z(K)$ with

$$u \equiv Z(K) = \frac{\alpha s^{\alpha-1} - (1-\alpha) s^{\alpha}}{\left[A (\tau_S w_S^*)^{\alpha} (\tau_N w_N^*)^{1-\alpha}\right]^{\sum_{k=1}^{K} (1-\theta)^k} \left(\Omega_S^{\alpha} \Omega_N^{1-\alpha}\right)^{(1-\theta)^K}} - \kappa. \tag{A.11}$$

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

$$\lim_{K \to \infty} Z(K) = \frac{\alpha s^{\alpha-1} - (1-\alpha) s^{\alpha}}{\left[A (\tau_S w_S^*)^{\alpha} (\tau_N w_N^*)^{1-\alpha}\right]^{\frac{1-\theta}{\theta}}} - \kappa, \tag{A.12}$$

as $\lim_{K \to \infty} \sum_{k=1}^{K} (1-\theta)^k = (1-\theta)/\theta$. The above equation no longer depends on $w_j \ \forall \ j \in \{S, N\}$, such that it is easy to infer that $\partial s / \partial \tau_j < 0 \ \forall \ j \in \{S, N\}$. Taking additionally into account that according to Eq. (A.7) the share of tasks performed domestically is proportional to the respective cost savings factor from offshoring $\Omega_j \leq 1 \ \forall \ j \in \{S, N\}$, Proposition 1 follows immediately. *QED*

B Empirical appendix

We source our data from the following providers: The data on (nominal) output at the industry level stem from the OECD's STAN database. The Herfindahl Index measuring industry competition for 2005 is taken from the Monopoly Commission's annual report to the Federal German government[31]. The annual import specific input output tables used in the calculation of the offshoring indices are part of the national accounts provided by the German Statistical Office[32].

[31] See http://www.monopolkommission.de/haupt.html.
[32] See 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 R&D shares in production and the import penetration ratios.

Table 4: *Summary statistics: estimation sample*

	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		
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		0.325	0.393
Import penetration growth 2004 - 2006		0.135	0.066
Herfindahl index ($\times$1.000) 2005		60.363	83.684
Research and Development Intensity in % 2004		2.640	2.570
Max. number of observations: 3,917			

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

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. 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%). 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. 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. Research and Development Intensity is Research and Development Spending over an industry's production value. Import penetration is total imports over domestic absorption.

Industry-level offshoring is calculated as described in Eq. (3). For the industries 15-16, 17-19, and 21-22 the OECD STAN bilateral trade database 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 the results of our preferred model in

Table 5: *Summary statistics: offshoring*

j	Industry	O_j	$\widehat{O}_j$	Training share	j	Industry	O_j	$\widehat{O}_j$	Training share
35	Other transport equip.	0.82	152.65	0.71	22	Publishing, printing	0.05	26.68	0.49
34	Motor vehicles	0.37	95.47	0.71	30	Office, computing mach.	8.17	23.76	0.69
27	Basic metals	2.15	86.07	0.62	15	Food, beverages	0.54	22.88	0.43
33	Medical, optical, precision instr.	0.61	52.01	0.62	29	Machinery, equipment	1.71	20.63	0.62
28	Fabricated metal prod.	0.30	39.38	0.49	20	Wood, cork prod.	1.02	19.23	0.49
25	Rubber, plastic	0.16	34.81	0.56	26	Non-metallic mineral prod.	0.31	13.31	0.45
24	Chemicals	0.83	34.32	0.74	36	Furniture	3.20	10.49	0.38
16	Tobacco	0.11	31.67	0.50	17	Textiles	4.63	8.03	0.29
18	Wearing apparel	5.60	30.45	0.58	32	Radio, television, comm.	9.83	5.36	0.61
19	Leather, luggage	7.70	29.27	0.56	31	Electrical machinery	1.52	4.19	0.66
21	Paper	0.49	27.79	0.43	23	Coke, refined petroleum	0.46	-52.44	0.70

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. Training share is the share of people reporting training participation. Industries are ranked in decreasing order according to the magnitude of sectoral offshoring growth. Industry names are abbreviated.

section 3.3 to be very similarly sized and highly statistically significant. For the calculation of the instrumental variables, we used OECD STAN imported intermediates from China for the IV country group. The imported intermediates are reported as aggregates for sectors 15-16, 17-19 and 21-22. We apportion these values to the individual sectors using shares of total imports, e.g. imported intermediates for 15-16 are split according to how many total goods imports industry 15 has in comparison to 16. For sector 33, there is no output data for Canada, which results in the IV for this sector to be calculated without Canada. Table 5 gives an overview of offshoring intensities across industries, both in levels and growth rates as well as industry level training rates.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Average marginal effect of:							
Offshoring growth	0.2412***	0.0688***	0.0619***	0.0639***	0.0869***	0.0788***	0.0717***
	(.0669)	(.008)	(.0145)	(.0215)	(.0144)	(.0210)	(.0182)
Age 30 - 39	−0.0057	−0.0057	−0.0310	−0.0019	−0.0033	0.0060	0.0155
	(.0195)	(.7832)	(.0237)	(.0202)	(.0200)	(.0191)	(.0286)
Age 40 - 49	−0.0526**	−0.0534**	−0.0602**	−0.0465*	−0.0443*	−0.0421*	−0.0107
	(.0231)	0.0480	(.0288)	(.0239)	(.0230)	(.0230)	(.0301)
Age 50 - 64	−0.1421***	−0.1416***	−0.1610***	−0.1401***	−0.1366***	−0.1366***	−0.0900**
	(.0279)	0.0020	(.0325)	(.0283)	(.0275)	(.0291)	(.0351)
Age 65+	−0.3348***	−0.3251***	−0.3732***	−0.3327***	−0.3347***	−0.3231***	−0.1737***
	(.0582)	0.0020	(.0652)	(.0593)	(.0592)	(.0623)	(.0558)
Female	−0.0684***	−0.0622***	−0.0990***	−0.0615***	−0.0648***	−0.0639***	−0.0441**
	(.0186)	0.0010	(.0187)	(.0184)	(.0187)	(.0224)	(.0189)
Married	−0.0091	−0.0080	−0.0067	−0.0123	−0.0117	−0.0015	−0.0087
	(.0215)	0.7373	(.0241)	(.0210)	(.0213)	(.0240)	(.0223)
Tenure	0.0031	0.0033	0.0043	0.0030	0.0031	0.0009	−0.0013
	(.0040)	0.4835	(.0042)	(.0040)	(.0040)	(.0032)	(.0052)
Tenure squared	−0.0001	0.0001	−0.0001	−0.0000	−0.0001	0.0000	0.0000
	(.0001)	0.6114	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Medium-skill	0.0362	0.0309	0.0259	0.0320	0.0357	0.0205	0.1122***
	(.0352)	0.4336	(.0339)	(.0353)	(.0364)	(.0352)	(.0416)
High-skill	−0.0001	0.0009	−0.0304	−0.0030	0.0002	0.0182	0.0261
	(.0212)	0.9550	(.0245)	(.0222)	(.0226)	(.0217)	(.0244)
Importance to have a career	0.0653***	0.0628***	0.0627***	0.0608***	0.0612***	0.0566***	0.0820***
	(.0206)	0.0080	(.0237)	(.0205)	(.0205)	(.0212)	(.0207)
Firm size 10 - 49	−0.0174	−0.0177	−0.0032	−0.0255	−0.0223	−0.0202	−0.1246***
	(.0210)	0.4216	(.0239)	(.0215)	(.0211)	(.0220)	(.0354)
Firm size 50 - 249	0.0523***	0.0497**	0.0668***	0.0480***	0.0481***	0.0401***	−0.0561***
	(.0165)	0.0120	(.0252)	(.0159)	(.0161)	(.0152)	(.0211)
Firm size 250 - 499	0.1011***	0.0972***	0.0843**	0.0894***	0.0990***	0.1016***	−0.0268
	(.0293)	0.0020	(.0388)	(.0300)	(.0288)	(.0309)	(.0247)
Firm size 500+	0.1259***	0.1151***	0.1000**	0.1104***	0.1139***	0.1117***	0.0267
	(.0236)	0.0020	(.0441)	(.0232)	(.0238)	(.0268)	(.0339)
Fixed term contract	−0.0904***	−0.0866**	−0.0744*	−0.0907***	−0.0908***	−0.1119***	−0.1039***
	(.0342)	0.0357	(.0440)	(.0342)	(.0347)	(.0339)	(.0305)
Temporary work	0.0339	0.0283	0.0576	0.0135	0.0399	0.0406	0.0375
	(.0533)	0.6933	(.0894)	(.0572)	(.0547)	(.0536)	(.0973)
New technology introduced	0.1679***	0.1658***	0.1493***	0.1660***	0.1705***	0.1719***	0.1237***
	(.0233)	0.0000	(.0286)	(.0235)	(.0233)	(.0233)	(.0270)
Current firm success (very) good	0.0463**	0.0477**	0.0490*	0.0457**	0.0472**	0.0485**	0.0514***
	(.0205)	0.0440	(.0269)	(.0199)	(.0201)	(.0214)	(.0196)
Industry Herfindahl index	0.0009***	0.0007***	0.0010***	0.0009***	0.0007***	0.0006***	0.0005***
	(.0003)	0.0020	(.0001)	(.0002)	(.0001)	(.0001)	(.0002)
Industry R&D intensity	0.0035	0.0073	0.0069**	0.0070**	0.0087**	0.0043	0.0059
	(.0044)	0.1139	(.0029)	(.0031)	(.0038)	(.0039)	(.0037)
Industry growth import penetration		0.5442***	0.6450***	0.6170***	0.5670***	0.3894***	0.4113***
		0.0000	(.1352)	(.0913)	(.1051)	(.1267)	(.1216)
KldB88 (2-digit) occupation FE	yes	yes	yes	yes	yes	yes	yes
Pseudo R-squared	.1401	.1830	.1409	.1419	.1399	.1284	.2221
Observations	3,888	3,917	3,888	3,845	3,805	3,421	2,623

Notes: The table shows average marginal effects from estimating variants of the Probit model specified in section 3.1. Column 2 shows the coefficients from a linear probability model and p-values based on a wild cluster bootstrap t-procedure in parenthesis. The reference category for firm size is 1 - 9 employees. 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. Research and Development intensity (for 2004) and import penetration are taken from the OECD STAN database. Standard errors are clustered at the industry level and shown in parentheses below the coefficients (except for column 2). Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

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