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Offshoring and non-monotonic employment effects across industries in general equilibrium*

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Abstract

We address the mismatch between existing theoretical models and standard empirical practice in the analysis of the labor market effects of offshoring. While theory focuses on one-sector or two-sector models, empirical studies exploit variation in offshoring across a large number of industries, typically including a linear offshoring term in the analysis. Thereby, these studies implicitly assume a monotonic relationship and ignore general-equilibrium effects across industries. We analyze the effects of offshoring across a continuum of industries with different shares of offshorable tasks that are linked through labor and capital markets in general oligopolistic equilibrium (GOLE). Our main result is that offshoring generates a hump-shaped pattern of employment changes across industries. While the relocation effect reduces employment in offshoring-intensive industries, labor demand in industries with a high prevalence of domestic production falls because of rising domestic wages and firm exits in general equilibrium. In the empirical part, we test the non-monotonic employment effects of offshoring across industries by focusing on Germany after the fall of the Iron Curtain. We find strong empirical support for the hump shape in the changes of employment across industries with different scopes for offshoring, which is almost entirely due to the extensive margin, underscoring the importance of establishment entry and exit. Finally, we discuss important implications for empirical and theoretical research arising from our study.

JEL codes: F12, F16, F23, J23, L13

Keywords: General oligopolistic equilibrium; Task offshoring; Offshoring and employment; Industry heterogeneity

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1 Introduction

Falling communication and transportation costs have triggered a dramatic rise in the international fragmentation of production processes (e.g. Johnson and Noguera, 2017). While offshoring firms are able to lower their production costs by exploiting international factor price differences, there are concerns about detrimental effects on domestic workers in high-wage countries. By now, a substantial body of empirical studies has analyzed the labor market effects of offshoring, yet no clear picture has emerged. The documented effects seem to be ambiguous and, contrary to the public concerns, mostly fairly small.[1] Theoretical work explains the ambiguity of offshoring on domestic labor demand by two opposing forces: a negative *relocation effect*, as domestic workers are replaced by foreign workers, and a positive *productivity effect*, as offshoring reduces firms' production costs and thus raises their demand for domestic labor.[2] However, existing theoretical models and standard empirical practice do not match each other well. Existing theories have studied the labor market effects of offshoring in various frameworks, but restricted attention to one-sector or two-sector models. In contrast, most empirical studies exploit variation in offshoring across a large number of industries for identification, typically including a linear offshoring term in the regression analysis. Thereby, these studies apply the one-sector or two-sector logic to many industries by linear extrapolation, implicitly assuming a monotonic relationship and treating each industry as a separate and independent unit of analysis.

In this paper, we argue that this approach can lead to misleading conclusions if industries are connected in general equilibrium. To arrive at this conclusion, we first set up a novel theoretical model, which features many industries and industry-level heterogeneity in the scope for offshoring. Industries are linked through labor and capital markets. In this framework, offshoring reduces labor demand both in (very) offshoring-intensive industries *and* in industries with little direct exposure to offshoring, while industries with an intermediate range of offshorable tasks gain employment. Thus, inter-industry reallocations arising from offshoring can generate a non-monotonic, hump-shaped pattern of changes in employment across industries. Focusing on West Germany and using the fall of the Iron Curtain as a quasi-natural experiment, we find robust empirical support for this hump-shaped pattern. In contrast, when we follow common practice and only include a linear offshorability term, we find small and statistically not significant effects of offshoring on domestic labor demand, in line with much of the existing empirical literature.[3] Finally, we discuss the broader implications for theoretical and empirical research arising from our study.

In the theoretical part, we build on the general oligopolistic equilibrium model (GOLE) introduced by Neary (2003, 2016). The GOLE framework is well equipped to study the question at hand. First, it provides a general equilibrium setting to study the labor market effects of offshoring while

[1] See Hummels et al. (2016) for a recent survey on nearly two decades of research on offshoring.

[2] See, for instance, Grossman and Rossi-Hansberg (2008) or Egger et al. (2015).

[3] One example in this respect is the well-known study by Amiti and Wei (2005), who analyze the relationship between employment growth and services (as well as material) offshoring at the industry level for the UK. They also note that "[...] no uniform pattern emerges between service outsourcing and employment" (p. 331). Interestingly, their scatter plot on this bivariate relationship follows a hump-shaped pattern (Figure 5 on p. 333).

incorporating industry heterogeneity in the scope for offshoring in a tractable way. Second, it allows for strategic interaction among firms together with positive profits in equilibrium that depend on the number of competitors within an industry – a prerequisite to endogenize capital (and thus firm) reallocations across industries. Thus, we believe that this model is particularly well suited for our purpose of investigating labor market effects of offshoring in a multi-industry framework.

In autarky, we abstract from any differences in unit production costs within and across industries, giving rise to a "featureless economy" (cf. Neary, 2003). However, in the open economy, production costs differ across industries due to their heterogeneity in the potential to shift parts of the production process to a foreign low-wage country. After fully characterizing the general equilibrium, we focus on the labor market effects of offshoring. Specifically, we focus on changes in industry-specific labor demand. The latter does depend on the industry's offshoring potential, but in a non-monotonic way. Negative employment effects arise in high *and* low offshoring-intensive industries while industries with an intermediate offshoring intensity expand their demand for domestic workers. While offshoring-intensive industries face a reduction in employment because of the relocation effect, labor demand in industries with a high prevalence of domestic production falls because of rising domestic wages in general equilibrium. In addition, capital owners have an incentive to alter their investment decision in the open economy, and firms enter (exit) in high (less) offshoring-intensive industries until profits are equalized in equilibrium. This so far unexplored channel creates (destroys) jobs in industries that do (not) engage in offshoring. Furthermore, we show that the hump shape in labor demand across industries becomes the more pronounced the larger the cost savings from offshoring are.

To take the key predictions of our theoretical model of offshoring to the data, we focus on West Germany and use the fall of the Iron Curtain as a quasi-natural experiment. This setting is well suited to study the labor market effects of offshoring as the opening-up and economic transformation of the formerly socialist countries into market economies greatly increased the opportunities of German firms to engage in offshoring. Indeed, the relocation of production of Germany to Central and Eastern Europe increased strongly in the aftermath of the fall of the Iron Curtain (e.g. Geishecker, 2006; Marin, 2006; Dustmann et al., 2014). We approximate pre-fall industry-level offshorability, i.e. offshoring potential, in a two-step procedure. First, we assign offshorability indicators developed by Blinder and Krueger (2013) to individual workers based on their disaggregate occupations. Second, we aggregate the individual-level data to the 3-digit industry level, thereby essentially exploiting the unequal distribution of occupations across industries prior to the fall of the Iron Curtain. Relying on this measure, we relate changes in total employment at the industry level (several years) after the fall of the Iron Curtain to pre-fall offshorability and find a statistically significant and robust hump-shaped relationship, as predicted by the theory. This relationship becomes more pronounced over longer horizons, and it is also visible if we consider changes in industry wage premia as an alternative outcome variable. By decomposing employment changes into the establishment intensive and extensive margin, we are able to show that the offshorability-related hump is almost entirely due to the extensive margin, underscoring the importance of establishment entry and exit for these differential growth rates across industries.

Having established the non-monotonic employment effects across industries, we describe the broader implications for both empirical and theoretical studies of offshoring. With respect to empirical studies, our results provide a cautionary tale about using industry-level variation to identify the (labor market) effects of offshoring. In particular, the standard reduced-form approach of inserting a linear offshoring or offshorability term in the regression – which implies the assumption of a monotonic relationship – may lead to misguided conclusions if these industries are connected in general equilibrium. Relatedly, our results suggest that the effects of offshoring may show up where they are least expected, i.e. in industries that do not engage (a lot) in offshoring. With respect to theoretical studies, we highlight implications specific to our model that have so far been neglected in the literature. For instance, we show that capital reallocations (via firm entries and exits) mitigate the economy-wide productivity effect of offshoring as firm entries occur in industries where only a small share of production is carried out domestically. Finally, as we document substantial inter-industry employment reallocations in response to an offshoring shock, our results also have implications for the magnitude of adjustment dynamics and costs. While modeling switching costs across industries is beyond the scope of our paper, those costs are known to be substantial in reality (e.g. Artuç et al., 2010; Dix-Carneiro, 2014).

Our paper contributes to several strands of the literature. By investigating the labor market effects of offshoring, our paper contributes to a large theoretical literature on offshoring in general equilibrium models. The discussion has mostly focused on labor-market outcomes (e.g. the skill premium, job destruction, etc.) and relied both on modifications of traditional trade models (e.g. Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008; Wright, 2014; Burstein and Vogel, 2017) and, more recently, on trade models that feature firm heterogeneity (e.g. Antràs and Helpman, 2004; Antràs et al., 2006; Sethupathy, 2013; Groizard et al., 2014; Egger et al., 2015). According to these papers, positive labor and welfare effects are more likely if the productivity effect dominates the relocation effect, the two major effects of offshoring that have been identified in the literature. However, less attention is drawn to the empirically relevant setting with many industries and industry heterogeneity in the possibilities to offshore.[4] This paper fills this gap and shows that the labor market effects arising from offshoring vary in a non-monotonic way across industries. Furthermore, as capital owners shift the resources towards industries which benefit above average from offshoring, we show that existing models exaggerate the productivity effect by ignoring linkages across industries in general equilibrium.[5]

Building on the general oligopolistic equilibrium model introduced by Neary (2003, 2016), our model also contributes to a growing literature that investigates (labor market) effects of globalization

[4] Rodríguez-Clare (2010) introduces offshoring into the Eaton and Kortum (2002) framework. While the continuum of goods (i.e. industries) differ with respect to their productivity, goods do not differ in their exogenous share of offshorable intermediate services.

[5] Groizard et al. (2014) also investigate how offshoring reallocates jobs across firms and industries, albeit limiting the analysis to two industries: a differentiated-good industry in which firms can offshore and a homogeneous-good non-offshoring industry. Hence, this model is not equipped to study the non-monotonic effects of offshoring across many industries.

in a GOLE setting (see, for instance, Neary, 2007; Bastos and Kreickemeier, 2009; Eckel and Neary, 2010; Egger and Etzel, 2012; Egger and Koch, 2012). However, in all of the existing papers, globalization is captured by trade in final goods while trade in intermediates (or tasks) is ignored. One exception here is Eckel and Irlacher (2017). However, their focus is on product line relocations within multi-product firms.

Finally, our paper also adds to the empirical literature on the labor market effects of offshoring. By evaluating the employment effects of offshoring at the industry level, our paper is most closely related to the early "Wave 1" of research (cf. Hummels et al., 2016, p.27) as in Feenstra and Hanson (1997, 1999) or Amiti and Wei (2005, 2006). However, we also speak to a large empirical literature of the recent "Wave 3" (cf. Hummels et al., 2016, p.38) that uses individual-level data, but still relies on industry-level variation in offshoring to identify the effects (e.g. Ebenstein et al., 2014). By using the fall of the Iron Curtain as a quasi-natural experiment and exploiting differences across industries in their ability to take advantage of the new offshoring opportunities due to their ex-ante differences in the share of offshorable tasks, we propose a novel empirical strategy to identify the labor market effects of offshoring.[6] This strategy is well suited to analyze outcomes over longer horizons. Importantly, what sets our analysis apart is that we allow for a non-monotonic labor demand effect across industries in response to a positive offshoring shock and that we have derived this central prediction in a framework that explicitly accounts for general-equilibrium feedback effects. Thereby, we address a concern raised by Hummels et al. (2016, p.47): "[...] few studies are about general equilibrium effects [...], more work can be done, and should be done, to bring empirics and theory closer together."

The remainder of our paper proceeds as follows. In Section 2, we set up the theoretical framework and derive the main results. In Section 3, we describe our data set, the empirical analysis, and the main findings. Section 4 discusses the implications of our results from a theoretical and empirical perspective. Section 5 concludes.

2 Offshoring in general oligopolistic equilibrium

2.1 Model description

We consider an economy that is endowed with L units of workers and K units of capital, which are supplied at perfectly competitive factor markets and fully mobile across a continuum of industries. Running a firm requires one unit of fixed capital input, and labor is used as a variable input in the production process. The product market side is modeled akin to the general oligopolistic equilibrium framework introduced by Neary (2003, 2016), in which firms have market power in their own industry and behave strategically against their local rivals, but take income, prices in other industries, and factor prices as given. In addition, we endogenize the number of firms along the

[6] The quasi-natural experiment implied by (different aspects of) the fall of the Iron Curtain has previously been exploited by, e.g., Redding and Sturm (2008), Brülhart et al. (2012), Glitz (2012), Dauth et al. (2014), and Dustmann et al. (2017). These papers mostly consider region-specific as opposed to industry-specific outcomes, and none of them focuses on offshoring.

lines of Egger and Etzel (2014) by assuming that each capital owner serves as an entrepreneur and receives firm profits in return to the capital investment.

Final goods production requires labor for the performance of tasks in the production process. We abstract from any technological differences among firms within and between industries. However, in the open economy, costs are industry-specific as industries differ in the share of offshorable and non-offshorable tasks, where the former type of tasks can be produced in a foreign low-wage country that is endowed with L^* units of workers.

In the following, we begin with a characterization of the closed economy before we investigate how offshoring leads to labor and capital reallocations across industries and how this affects industry-level employment.

2.2 The closed economy

Following Neary (2003, 2016), we assume an additively separable utility function defined over a continuum of industries z, where consumer c maximizes utility

$$U[x_c(z)] = \int_0^1 [ax_c(z) - \frac{1}{2}bx_c(z)^2]dz \tag{1}$$

subject to a budget constraint $\int_0^1 p(z)x_c(z)di \leq I_c$, where I_c is consumer c's income.[7] Aggregate demand $x(z)$ of a firm selling at price $p(z)$ is then determined by the following inverse demand:

$$p(z) = \frac{1}{\lambda}\left[a'_{aut} - bx(z)\right], \tag{2}$$

where $a'_{aut} = (K + L)a$ and λ is the sum over each consumer's marginal utility of income, i.e. the Lagrange multiplier attached to the budget constraint.[8] As it is standard in the literature, we choose the marginal utility of income as the numèraire and set λ equal to one (see Neary, 2016, for further discussion). Firms maximize profits with respect to output $y(z)$ under Cournot competition among $n(z)$ homogeneous firms, which entails

$$y(z) = \frac{a'_{aut} - c(z)}{b[n(z) + 1]} \quad \text{and} \quad p(z) = \frac{a'_{aut} + n(z)c(z)}{n(z) + 1} \tag{3}$$

for output and prices, respectively, where variable production costs in industry z are denoted by $c(z)$.[9]

[7] Solving the utility maximization problem yields $p(z) = \frac{1}{\lambda_c}[a - bx_c(z)]$, where $\lambda_c = \frac{a\sigma_1 - bI_c}{\sigma_2}$ denotes the marginal utility of income of consumer c, which depends on the first and second moments of prices, $\sigma_1 = \int_0^1 p(z)dz$ and $\sigma_2 = \int_0^1 p(z)^2dz$, respectively. Total demand is finally derived by aggregation over all consumers, i.e. all workers L and owners of capital K.

[8] Throughout the subsequent analysis, we assume both non-satiation and participation and only focus on parameter constraints such that both conditions are fulfilled. Participation requires a positive marginal utility of income for each agent c while non-satiation requires positive demand regarding each agent's consumption of any good z. Put differently, it requires positive income for all agents and sufficiently small price differences between all goods.

[9] Profit of firm i in industry z is given by $\pi_i(z) = [p(z) - c(z)]y_i(z)$. The first-order condition for scale is given by $\frac{\partial \pi_i(z)}{\partial y_i(z)} = p(z) - c(z) + \frac{\partial p(z)}{\partial y_i(z)}y_i(z) = 0$. By symmetry, we have $y_i(z) = y_j(z) = y(z)$ and, thus, per-firm output is given

Without opportunities for offshoring, variable labor costs $c(z)$ are symmetric across industries, and we can drop industry indices for the autarky equilibrium. To determine the number of firms, note that capital owners aim to maximize their returns to investment. This implies that profits are equalized across industries to make capital owners indifferent in their decision in which industry they should start a firm. Capital market clearing requires $K = \int_0^1 n(z)dz$, and hence, with a unit mass of industries, we get $n = K$. Finally, variable production costs in autarky are determined by the domestic labor costs, i.e. $c(z) = c = w_{aut}$. To compute domestic wages in autarky, we substitute $y(z)$ from Equation (3) into the labor market clearing condition $L = \int_0^1 n(z)y(z)dz = ny$ and derive

$$w_{aut} = a'_{aut} - \frac{b(n+1)L}{n}. \tag{4}$$

With equilibrium wages at hand, it is straightforward to compute the autarky values for output $y_{aut} = L/n$, prices $p_{aut} = a'_{aut} - bL$ and profits $\pi_{aut} = b(L/n)^2$.

2.3 The open economy

In the following, we introduce opportunities to offshore production in a parsimonious way similar to Egger et al. (2015). Specifically, firms can shift parts of their production process to the foreign offshore destination. Without foreign capital and abstracting from capital owners to invest in the foreign country, foreign workers can only be employed in offshored task activities of domestic firms. Their wage rate depends on the magnitude of offshoring and falls to zero in the absence of offshoring. Foreign workers share the same preferences as domestic consumers, and, by abstracting from any costs to ship final goods, inverse demand is similar to Equation (2) in the closed economy, however with $a' = (K + L + L^*)a$.[10] Since foreign labor income is spent on domestic products, opening the economy leads to a positive demand effect ($a' > a'_{aut}$), which is the same across all industries.

The extent to which production can be relocated abroad depends on the industry-specific prospects for offshoring. We assume that the share of tasks that can be produced offshore is determined by the industry index z. For our baseline model, we assume the following cost function, which arises from a Leontief production function, where output is produced by combining z offshorable and $1-z$ non-offshorable tasks over the unit interval:

$$c(z) = z(w^*\tau) + (1-z)w, \tag{5}$$

with w^* denoting labor costs in the foreign country and τ representing iceberg-type transport costs to ship foreign produced tasks to the domestic country.[11] In Appendix A, we clarify that our results do not depend on the specific modeling of production costs. In particular, we show that the results are robust to (i) considering a Cobb-Douglas production technology, (ii) introducing fixed costs of offshoring that generate a cut-off industry $0 < \widetilde{z} < 1$, at which firms start to offshore, and

by $y(z)$ in Equation (3). Substituting this into inverse demand in Equation (2) gives prices in industry z.

[10] In the open economy, we further have $\lambda = \sum_c \lambda_c = (a'\sigma_1 - bI)/\sigma_2$ and $I = \sum_c I_c = wL + \int_0^1 n(z)\pi(z)dz + w^*L^*$.

[11] Throughout our analysis, all foreign variables are marked with an asterisk.

(iii) allowing for a more general production technology, where offshoring is not linearly increasing in z.

The cost structure in Equation (5) captures in a simple way the fact that industries differ in the share of offshorable and non-offshorable tasks and thus in the prospective cost savings from offshoring. Before discussing the labor market effects of offshoring in our framework, we characterize the short-run and long-run equilibrium. In the short run, we assume that the number of firms in each industry is given by the closed-economy allocation of capital, whereas in the long run, we allow investors to reallocate their capital.[12]

2.3.1 Free labor mobility among industries – short run

To derive the equilibrium for a given allocation of capital, we determine domestic and foreign wages by making use of the labor market clearing conditions in both countries:

$$L = \int_0^1 L(z)dz = \int_0^1 (1-z)ny(z)dz \quad \text{and} \quad L^* = \tau \int_0^1 L^*(z)dz = \tau \int_0^1 zny(z)dz. \tag{6}$$

By substituting optimal output from Equation (3) into the labor market clearing conditions, we compute equilibrium wages for a given number of firms, indicated by subscript s (for short run), as

$$w_s = a' + 2\frac{b(n+1)}{n}\left(\frac{L^*}{\tau} - 2L\right) \quad \text{and} \quad w_s^* = \frac{1}{\tau}\left[a' + 2\frac{b(n+1)}{n}\left(L - 2\frac{L^*}{\tau}\right)\right]. \tag{7}$$

While the domestic wage rate decreases in L, it increases in the effective size of foreign labor supply L^*/τ. A larger pool of foreign workers reduces labor costs in the offshore location, and thus, higher cost savings from offshoring arise. This productivity effect of offshoring has a positive effect on domestic wages. The intuition behind this result is as follows: lower production costs abroad allow firms to charge lower prices and increase outputs. Hence, there is an increase in the economy-wide demand for labor, which drives up domestic wages.

Having solved for domestic and foreign labor costs, we are now equipped to determine the equilibrium outcome for industry-specific output levels, prices, and profits, which entails:

$$y_s(z) = \frac{2}{n}\left[(2-3z)L - (1-3z)\frac{L^*}{\tau}\right], \tag{8}$$

$$p_s(z) = a' + 2b(1-3z)\frac{L^*}{\tau} + 2b(3z-2)L, \quad \text{and} \tag{9}$$

$$\pi_s(z) = \frac{4b}{n^2}\left[(2-3z)L - (1-3z)\frac{L^*}{\tau}\right]^2. \tag{10}$$

To ensure positive outputs in all industries, i.e. $y_s(0) > 0$, and incentives for efficiency-seeking offshoring, i.e. $w > w^*\tau$, we impose the following parameter restriction: $2L \geq L^*/\tau \geq L$. Through-

[12] The endogeneity of capital investment as a criterion to distinguish the long run from the short run is common in the literature (see, for instance, Blanchard and Giavazzi, 2003 or Egger and Etzel, 2014 in the GOLE framework). Moreover, Melitz and Ottaviano (2008) only allow for endogenous firm entry in their long-run equilibrium.

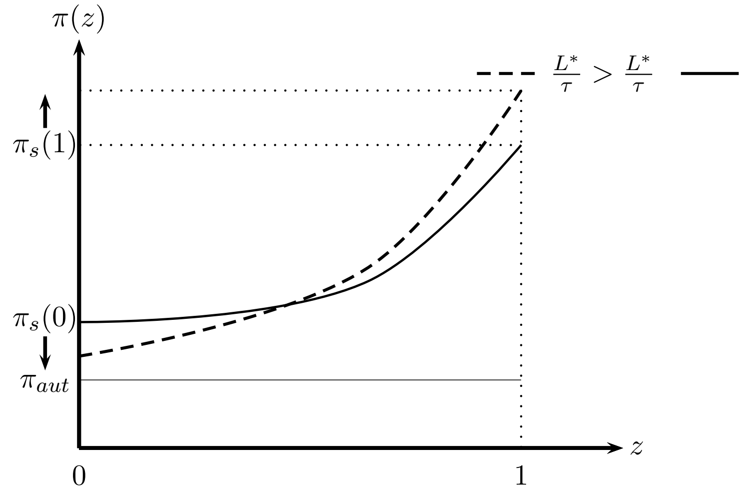


Figure 1: Profits across industries for different levels of L^*/τ.

out our analysis, we will vary the size of foreign effective labor L^*/τ within the upper and lower bound. This corresponds to changes in the potential cost savings from offshoring. With $L^*/\tau = L$, savings from offshoring vanish since $w = w^*\tau$, and hence, firms in all industries generate identical profits. However, if $L^*/\tau > L$, industry-specific cost savings from offshoring arise and are largest in offshoring-intensive industries.

From inspection of Equations (8) and (9) together with $2L \geq L^*/\tau \geq L$, we can infer that firms in industries with a higher share of offshorable tasks set lower prices and sell at a larger scale.[13] To investigate the impact of offshoring on firm profits across industries, we compare the results to autarky and summarize the findings in Figure 1.[14] This figure depicts a case where all industries gain from offshoring. However, our framework also captures cases in which some industries may lose in the open economy despite the new opportunities arising from offshoring. To show this result, we compare profits in the industry with the lowest offshoring potential $z = 0$ to the respective profits under autarky:

$$\Delta_s(0) \equiv \pi_s(0) - \pi_{aut} = \frac{4b}{n^2}\left[\left(2L - \frac{L^*}{\tau}\right)^2 - L^2\right]. \tag{11}$$

Evaluating $\Delta_s(0)$ at the upper bound for the effective size of foreign labor $L^*/\tau = 2L$, we end up at a situation where industries with low offshoring potentials lose from opening up the economy since $\Delta_s(0)|_{L^*/\tau=2L} = -4b(L/n)^2 < 0$. More generally, we are able to show that the difference in profits arising from offshoring decreases with falling offshoring costs τ, i.e. $\partial\Delta_s(0)/\partial\tau =$

[13] The respective derivatives are given by: $\partial p_s(z)/\partial z = -6b(L^*/\tau - L) < 0$ and $\partial y_s(z)/\partial z = 6/n(L^*/\tau - L) > 0$.

[14] To derive this figure, we compute the first and second derivative of $\pi(z)$ with respect to z: $\frac{\partial \pi(z)}{\partial z} = \frac{b}{n^2}\left[24\left((2-3z)L - (1-3z)\frac{L^*}{\tau}\right)\left(\frac{L^*}{\tau} - L\right)\right] > 0$ and $\frac{\partial^2 \pi(z)}{\partial z^2} = \frac{72b}{n^2}\left(\frac{L^*}{\tau} - L\right)^2 > 0$.

$8b/(n^2)\left[2L - L^*/\tau\right] L^*/\tau^2 > 0$. Differentiating profits with respect to τ, we get

$$\frac{\partial \pi_s(z)}{\partial \tau} = \frac{8b\left[(2-3z)\,L - (1-3z)\,\frac{L^*}{\tau}\right](1-3z)\,L^*}{n^2\tau^2} \gtrless 0. \tag{12}$$

Thus, we can conclude that profits in industries $z \in [0; 1/3[$ are reduced following a liberalization process, whereas firms in industries $z \in]1/3; 1]$ expand profits. The reason behind this result is that in industries with only few tasks being offshorable, the benefits from falling offshoring costs are moderate. However, those industries are hurt by general-equilibrium effects on the domestic labor market as the productivity effect of offshoring raises domestic labor costs (see above). This increase in domestic factor prices especially hits industries where the share of domestic production is relatively high.

The result that industries are affected differently from opening the economy to offshoring as well as from falling offshoring costs is crucial for the understanding of how investors will reallocate their capital. In the subsequent part, we will allow capital to be mobile across industries and investigate the labor market outcome in a long-run equilibrium where the number of firms per industry is determined endogenously.

2.3.2 Free capital mobility among industries – long run

To solve for the equilibrium with free capital mobility, we first have to specify an industry-specific number of firms $n(z)$. In equilibrium, capital is reallocated until owners are indifferent in their investment decision in which industry to run a firm. Hence, to make investors indifferent, profits must be equalized across all industries, i.e. $\pi(z) = \pi = \pi(0)$. Substituting profits into the latter condition, we determine the equilibrium number of firms in z as:

$$n(z) = \frac{(a' - w)n(0) + z[n(0) + 1](w - w^*\tau)}{a' - w}. \tag{13}$$

In a next step, we insert Equation (13) into the capital market clearing condition $K = \int_0^1 n(z)dz$ to derive the equilibrium number of firms in the purely domestically producing industry:

$$n(0) = \frac{2(a' - w)K - (w - w^*\tau)}{2a' - w - w^*\tau}. \tag{14}$$

To compute equilibrium wages with free capital mobility, we substitute Equations (13) and (14) into the domestic and foreign labor market clearing conditions from Equation (6):

$$w = \frac{1}{K}\left[a'K - (4K+1)bL + \frac{(2K-1)bL^*}{\tau}\right] \quad \text{and} \quad w^* = \frac{1}{\tau K}\left[a'K + (2K-1)bL - \frac{(4K+1)bL^*}{\tau}\right]. \tag{15}$$

Finally, we insert equilibrium wages into Equation (13) to derive the industry-specific number of firms in terms of exogenous variables:

$$n(z) = \frac{2K\left[(2-3z)L - (1-3z)L^*/\tau\right]}{L + L^*/\tau}. \tag{16}$$

Differentiating Equation (16) with respect to z, i.e. $\partial n(z)/\partial z = 6K(L^*/\tau - L)/(L + L^*/\tau) > 0$, we can conclude that the equilibrium number of firms is increasing in the share of offshorable tasks. To be more specific, comparing the number of firms to the autarky situation, it is easily shown that the number of firms in industry $z = 1/2$ is unchanged while in industries $z > 1/2$ ($z < 1/2$) firms enter (exit). Thus, with mobile capital, firms enter (exit) in high (less) offshoring-intensive industries. This movement of firms ensures that the no-arbitrage condition for capital is fulfilled, leading to identical firm profits across all industries: $\pi = bK^{-2}(L + L^*/\tau)^2$.[15] These competitive effects from offshoring reduce average profits compared to a situation with a fixed number of firms per industry.[16]

2.4 Industry-specific labor market effects of offshoring

Having characterized the open-economy equilibrium, we discuss the labor market effects of offshoring. We focus on the change in employment across heterogeneous industries. In particular, we derive two main novel predictions specific to our model that are taken to the data in the subsequent section. To do this, we compute industry-specific demand for domestic labor in a first step:

$$L(z) = (1-z)y(z)n(z) = 2(1-z)\left[(2-3z)L - (1-3z)L^*/\tau\right]. \tag{17}$$

In Figure 2, we plot labor demand per industry under autarky L_{aut} as well as $L(z)$ from Equation (17) for the open-economy scenario. We draw $L(z)$ for three different effective sizes of the foreign labor market L^*/τ within the range of possible values that are defined above.

The dotted line represents a scenario without any cost savings from offshoring in equilibrium. As $L^*/\tau = L$ implies $w = w^*\tau$, production costs are identical in all industries. In this case, output is the same across all industries, and domestic labor demand decreases monotonically in z due to the relocation effect. In comparison to autarky, $L(z)$ increases (decreases) in industries $z < 1/2$ ($z > 1/2$). One can think of this benchmark case as a scenario where general-equilibrium effects across industries do not play a role. To be more specific, with $L^*/\tau = L$, only the relocation effect is active, while there is no productivity effect of offshoring on domestic wages and no capital reallocation. Only for this scenario, a linear relationship between offshorability and labor demand across industries, as employed in many previous empirical studies, would be appropriate (more on this below).

[15] From $\partial n(z)/\partial \tau = 6K(1-2z)LL^*\tau^{-2}(L + L^*/\tau)^{-2} \lesseqgtr 0$, we can furthermore conclude that in industries $z > 1/2$ ($z < 1/2$), the number of firms increases (decreases) when offshoring costs fall.

[16] Comparing average profits for a given allocation of capital $\widetilde{\pi}_s = 4b\left[L^2 + (L^*/\tau)^2 - LL^*/\tau\right]n^{-2}$ with average profits under firm entry/exit entails: $\widetilde{\pi}_s - \pi = 3bK^{-2}(L^*/\tau - L)^2 > 0$.

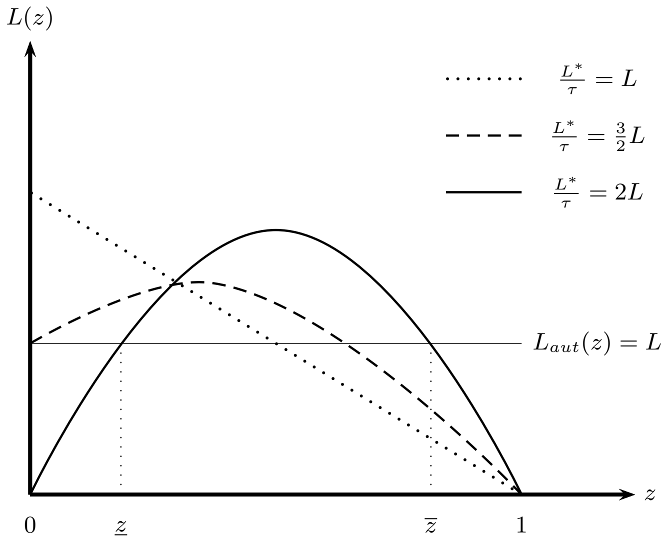


Figure 2: Labor demand across industries for different levels of L^*/τ

Starting from this edge case, we induce general-equilibrium effects across industries by increasing the effective supply of foreign labor (increase in L^* or decrease in τ) and, thus, reducing foreign wages. By doing so, we widen the gap between domestic and foreign wages and, hence, increase the potential cost savings from offshoring. From the previous section, we already know that this generates differential effects across industries depending on their respective offshorability. While firms in industries with a high share of offshorable tasks benefit from lower production costs abroad, firms in industries with mostly domestic production face even higher costs because of rising domestic wages (due to the productivity effect of offshoring).

The dashed line is drawn for intermediate cost savings from offshoring, whereas the solid line represents a scenario where cost savings from offshoring are the largest. Comparing this to the benchmark scenario reveals that the relationship between the offshorability of an industry and its demand for domestic labor is not monotonic any longer. It turns out that the non-monotonicity is getting the more pronounced the larger the effective size of the foreign market is, resulting in a hump-shaped pattern when cost savings are the highest. This is the main result of our theory, and we will focus on the intuition behind it in the following.

When cost savings from offshoring are very high, our model predicts that not only jobs in offshoring-intensive industries are lost, but also supposedly secure jobs in non-offshoring intensive industries. Figure 2 reveals a lower labor demand in comparison to autarky in industries with an offshorability index $z \in [0; \underline{z}[$ and $z \in]\overline{z}; 1]$. While the loss of jobs in industries with a high offshorability is obviously due to a strong relocation effect, the decline in labor demand in industries with a low offshorability is less trivial. What drives down labor demand in those industries are general-equilibrium effects on both the labor and the capital market. As explained before, the economy-wide productivity effect of offshoring increases domestic wages, thus hitting especially predominantly domestic industries. This leads to heterogeneous returns to capital across industries, which induce capital flows towards offshoring-intensive industries. Hence, labor demand in industries $z \in [0; \underline{z}[$ is reduced because of firm exit. Evaluating Equation (16) in industry $z = 0$ at $L^*/\tau = 2L$

implies that the number of firms is zero. Obviously, this drives down labor demand to zero in that industry (cf. Equation 17).[17]

We summarize our findings in the following first testable prediction.

Proposition 1 *Industry-specific prospects for offshoring in combination with general-equilibrium linkages create a non-monotonic relation between offshorability and labor demand per industry. While labor demand in offshoring-intensive industries is reduced via the relocation effect, jobs in non-offshoring industries disappear because of feedback mechanisms in general equilibrium.*

A second testable prediction relates to the evolution of the non-monotonic relationship between offshorability and industry-specific labor demand into the final hump-shaped pattern. From the discussion above, we conclude that the non-monotonicity gets the more pronounced the stronger the general-equilibrium effects are. Hence, a continuous improvement in the access to cheap foreign labor ($L^* \uparrow$) or a decline in offshoring costs over time ($\tau \downarrow$) strengthen the general-equilibrium linkages and lead to the hump-shaped pattern illustrated in Figure 2.

Proposition 2 *The non-monotonic relationship between the offshorability of an industry and its demand for labor gets more pronounced if the access to cheap foreign labor increases or offshoring costs decrease over time.*

3 Empirical analysis

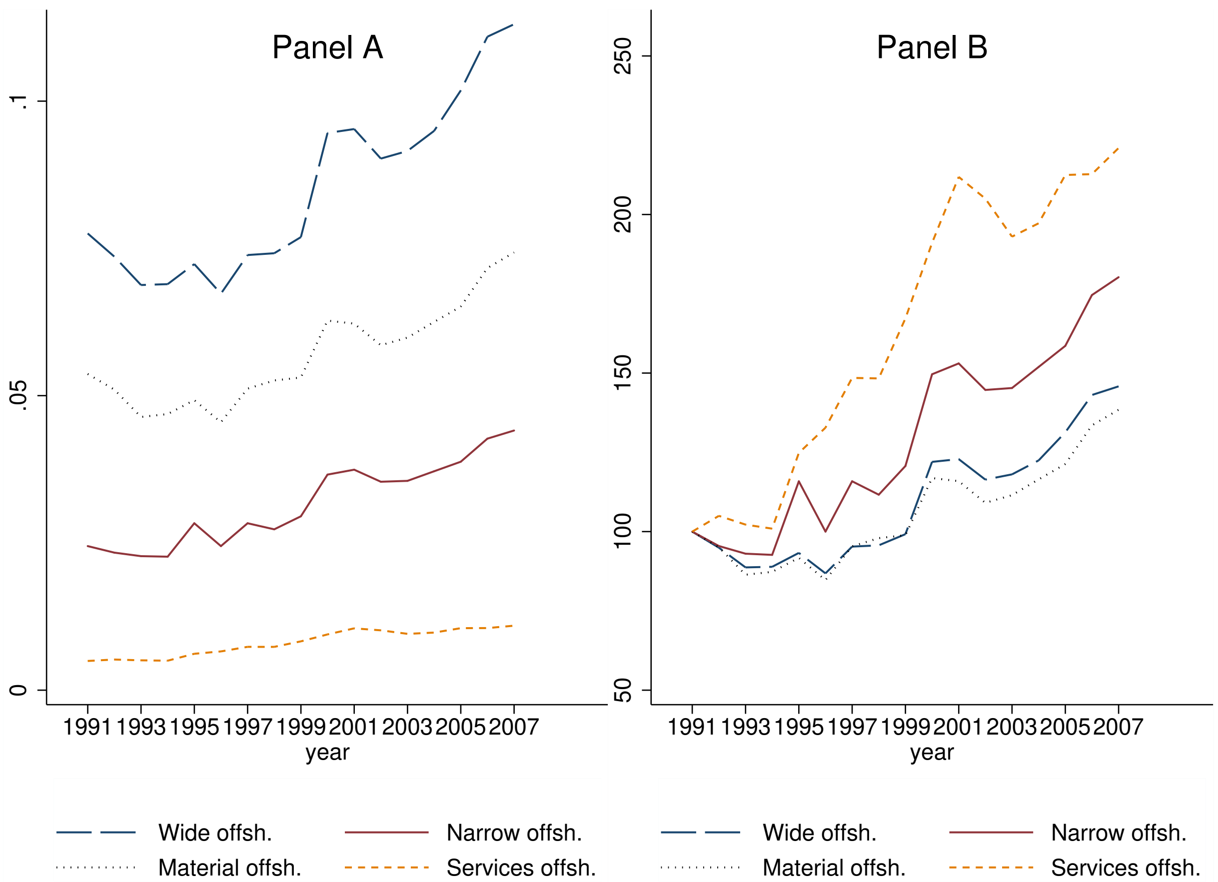
3.1 Empirical setting

To take the two key predictions of the theoretical model to the data, we consider the West German experience in the wake of the fall of the Iron Curtain. This setting seems to be particularly fitting and empirically attractive for a number of reasons. First, the opening-up and economic transformation of the formerly socialist countries into market economies, most of which are just at Germany's doorstep, greatly, and unexpectedly, increased the opportunities of German firms to engage in international production fragmentation. In the context of the theoretical model, this process can be interpreted as giving access to a newly available foreign low-wage labor pool L^*. Moreover, since these countries are close by, trade costs with them are considerably lower than trade costs with countries that can offer a similarly skilled and yet comparatively low-paid workforce such as, say, in "Factory Asia". Also, trade costs further declined over time. Trade integration with the Central and Eastern European countries started with the Europe Agreements in the early and mid 1990s and culminated in the EU accession of several of these countries in the years 2004, 2007, and 2013.[18] Thus in the context of the model, this development implied a decline in offshoring costs τ. Note

[17] In the case of intermediate cost savings and thus intermediate factor price differences between the two economies (dashed line), industry-specific labor demand in mostly domestic industries is still higher compared to autarky. The reason behind this result is the additional demand from foreign workers, which outweighs the general-equilibrium effects.

[18] Estonia, Latvia, Lithuania, Poland, the Czech Republic, Slovakia, Slovenia, and Hungary joined in 2004; Bulgaria and Romania joined in 2007; and Croatia joined in 2013.

Figure 3: The development of offshoring over time



Notes: Offshoring=share of imported intermediates in industry total output. Wide offshoring includes all imported intermediates from abroad. Narrow offshoring restricts attention to imported intermediates from the same 2-digit industry. Material offshoring only includes imported intermediates from manufacturing industries (NACE Rev. 1 codes 15–37). Services offshoring only includes imported intermediates from commercial service industries (NACE Rev. 1 codes 64–67 and 71–74). Panel A displays level values of the offshoring measures. Panel B displays index values, where all measures have been normalized to 100 for the year 1991. Output-weighted average over 2-digit industries.
Source: German input-output tables, own calculations.

that, from the perspective of the West German economy, German reunification had very similar implications.[19]

Previous research has indeed shown that offshoring of Germany to Central and Eastern Europe increased rapidly in the aftermath of the fall of the Iron Curtain and analyzed some of its (labor market) consequences (e.g. Geishecker, 2006; Marin, 2006; Dustmann et al., 2014). Also in an international comparison, Johnson and Noguera (2017) highlight Germany as one example of an advanced economy with a particular large decrease in the value added to export (VAX) ratio, a measure of international production fragmentation, over the period 1970 to 2009 (without breaking this up by destination region and time periods, however). This decline was considerably larger than the ones experienced by, say, the US, Japan, the UK, or France over the same period of analysis.

[19] We will return to the issue of German reunification below in Subsection 3.5.

As will become clear in the description of the empirical approach below, it is not essential for our analysis that increased offshoring of West German firms has (exclusively) taken place in Eastern Europe. What we exploit is just the fact that there was a positive offshoring shock after 1988.

Figure 3 further illustrates the increase in Germany's offshoring intensity over time, where the offshoring indicators are constructed from German input-output tables as the share of imported intermediates in (2-digit) industry total output.[20] Four different measures are constructed: wide offshoring, narrow offshoring, material offshoring, and services offshoring. Panel A displays the development of the nominal values of these indices, while Panel B shows the growth of index values, where all measures have been normalized to 100 for the year 1991.[21] Offshoring stayed fairly flat or even slightly decreased up to the mid 90s, but increased substantially thereafter. There was another dip in the wake of the burst of the dotcom bubble in 2001, but the rise of offshoring continued from 2003 onwards. Overall, wide offshoring increased from 7.8% to 11.3% (by 46%) and narrow offshoring from 2.4% to 4.4% (by 80%). One can also see that services offshoring, while still of limited quantitative importance compared to material offshoring in level terms, had the largest growth rates between 1991 and 2007.

3.2 Empirical approach and specification

While the fall of the Iron Curtain constitutes an unforeseen shock to the West German economy as a whole, we exploit the fact that different industries were prepared to varying degrees to take advantage of the new offshoring opportunities due to their ex-ante differences in the share of offshorable tasks.

Specifically, we relate industry-level labor market outcomes (several years) after the fall of the Iron Curtain to the pre-fall share of offshorable tasks. In line with the theoretical model's prediction, we allow this effect to be non-monotonic. We estimate different versions of the following regression model:

$$\Delta \ln Emp_{jh} = \alpha + \beta_1 Offshorability_{j,1988} + \beta_2 Offshorability^2_{j,1988} + X'_{j,1988}\gamma + u_{jh}, \qquad (18)$$

where j denotes the 3-digit industry and h the time horizon. As our main outcome variable, we consider the change in log employment between 1988 and year $1988+h$, where we let h vary up to a maximum of 26 years (given that the final year of our sample is 2014). In addition to the quadratic term of $Offshorability$, whose exact construction we explain in the data section below, we include a rich set of start-of-period control variables $X_{j,1988}$: a dummy that equals one if the industry is part of the manufacturing sector (such that we only exploit variation within the manufacturing and the non-manufacturing sectors, respectively); employment shares by age[22]; employment shares by

[20] The figures display the output-weighted average over all 2-digit industries.

[21] Due to the limited availability of comparable input-output tables, these indices can only be constructed for the years 1991 to 2007. Moreover, they refer to the whole of (unified) Germany, while the subsequent empirical analysis will restrict attention to West Germany only.

[22] We distinguish five age groups: 18–25; 26–35; 36–45; 46–55; and 56–65.

education[23]; female employment share; foreign employment share; and a quadratic term of log total employment.[24] To allow for a potential serial correlation of the error term within broader industry groups, we cluster standard errors at the 2-digit industry level. Note that, since this specification is estimated in first differences, any trends affecting all industries of the economy are captured by the constant. Likewise, the manufacturing dummy accounts for any diverging trends between the manufacturing sector and the rest of the economy.

Our empirical strategy, which is motivated by, and hence closely following, the predictions of the theoretical model, differs from two existing existing strands of the related literature. On the one hand, many studies on the labor market effects of offshoring that also rely on industry-level variation often use a fixed-effect specification of the type $Y_{(i)jt} = \eta_j + \beta Offshoring_{jt} + X'_{jt}\gamma + u_{jt}$ (cf. Hummels et al., 2016). Importantly, according to our reading of the literature, all of the existing studies have employed only a linear offshoring term, which is at odds with our theoretical predictions. In addition, these studies generally regress labor market outcomes (either at the individual, firm, or industry level) on contemporaneous, realized offshoring, facing the challenge of finding suitable exogenous variation in offshoring. In contrast, we regress the change in log employment on ex-ante offshorability, i.e. offshoring potential, which is a predetermined variable. As such, we essentially estimate a reduced form where the outcome is regressed on the instrument.[25] Note that, even if we wanted to, we would not be able to estimate the full two-stage least squares IV model as we do not have a proper measure of realized offshoring at the 3-digit industry level. A further advantage of our set-up is that we can easily look at outcomes over various horizons.

On the other hand, Dauth et al. (2014, 2016) have recently analyzed the effect of trade with Eastern Europe and China on the German labor market, applying the approach pioneered by Autor et al. (2013, 2014). These studies differ from ours in important dimensions. First of all, their focus is on final goods trade as opposed to offshoring. Secondly, they exploit heterogeneous changes in comparative advantage across industries that originate in those countries (the "supply shock" element of growing import exposure), while we exploit ex-ante differences across domestic industries in their prospects for fragmenting production.

3.3 Data and measurement

3.3.1 German social security data

The main data set used in the empirical analysis is the Sample of Integrated Employment Biographies (SIAB).[26] It is a 2-percent random sample of administrative social security records, which

[23]We distinguish five education groups: Missing; Lower secondary school or less without vocational training; Lower secondary school or less with vocational training; Abitur (with or without vocational training); University or more.

[24]Summary statistics of the dependent and the explanatory variables are given in Table 9 in Appendix B.2.

[25]A similar approach was chosen, e.g., by Autor and Dorn (2013) in their study on the growth of service occupation employment, where the ex-ante share of routine workers serves as a predictor for the subsequent adoption of information technology.

[26]More precisely, this study uses the weakly anonymous Sample of Integrated Labour Market Biographies (years 1975–2014). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access

is assembled from different sources and provided by the Institute for Employment Research at the German Federal Employment Agency. The population is the universe of individuals who had one of the following statuses at least once during the observation period: employed in a job covered by social security; marginally employed (recorded from 1999 onwards); participation in an employment or training measure (recorded from 2000 onwards); receipt of benefits; registered as as job seeker with the Federal Employment Agency (recorded from 2000 onwards). This includes roughly 80 percent of all German employees. Notable exceptions are the self-employed and civil servants. For the sampled individuals, the data set covers the entire employment biography with respect to the covered statuses and is exact to the day.

The information provided for the employment spells includes – apart from other characteristics – the occupation of the individuals following the KldB1988 classification of the German Federal Employment Agency. Furthermore, although the original industry classification changes a few times during the period of observation, the Research Data Centre provides a consistent series of (imputed) three-digit NACE Rev. 1 codes, which is used in the present analysis (cf. Eberle et al., 2011).

We restrict attention to regular workers between 18 and 65 years of age. That is, we discard apprentices, trainees, marginal employed in so-called "mini jobs", home workers, individuals in partial retirement, as well as individuals who are currently on leave. The data set does not contain information on the hours of work, but only whether the job is part-time or full-time. We generate a measure of full-time equivalent workers by weighting observations in part-time jobs by 18/39 (and observations in full-time jobs by 1).[27]

For our empirical analysis, we keep observations for the 30th of June of every year and aggregate the individual-level data to the 3-digit industry level.

3.3.2 Measuring offshorability

The literature pioneered by authors such as Leamer and Storper (2001), Levy and Murnane (2004), and Blinder (2006) has converged towards the notion that a job's offshorability, i.e. its susceptibility to being relocated to a foreign country, does not primarily depend on the worker's skill level, but rather on the type of tasks performed on the job. Since tasks are most closely related to the occupation of a worker, offshorability is typically treated as an occupation-level characteristic. Conforming to this literature, we approximate industry-level offshorability in a two-step procedure. First, we assign offshorability indicators to individual workers based on their disaggregate occupations.[28] Second, we aggregate the individual-level data to the 3-digit industry level, thereby essentially exploiting the unequal distribution of occupations across industries. For our most parsimonious and preferred occupation-level offshorability measure, which is a 0/1 dummy distinguishing non-offshorable and offshorable occupations (as we explain below), the industry-level offshorability measure boils down to the share of offshorable jobs in an industry, measured prior to the fall of

(project fdz1227/1228). See Antoni et al. (2016) for a detailed description of the data.

[27] A standard working week of full-time workers amounts to 39 hours while the cut between part-time and full-time jobs in the data is at 18 weekly hours.

[28] In the data, we distinguish between 335 3-digit occupations in the German KldB 1988 classification.

the Iron Curtain in 1988. A further attractive feature of this operationalization is that it is closely related to our variable z in the theoretical model.

To measure occupation-level offshorability, we use the indicator proposed by Blinder and Krueger (2013), which is based on professional coders' assessment, as our preferred measure because it offers a number of advantages. First, it was specifically designed to capture whether the nature of the job "allows the work to be moved overseas in principle" (Blinder and Krueger, 2013, p. S99). Thereby, secondly, this measure avoids a potentially too large overlap with other task indicators (such as routineness), which might also capture susceptibility to automation (cf. Autor, 2013). Third, Goos et al. (2014) have used this measure before in a European context and have found that it correlates well (and better than alternative measures) with actual offshoring activities.[29]

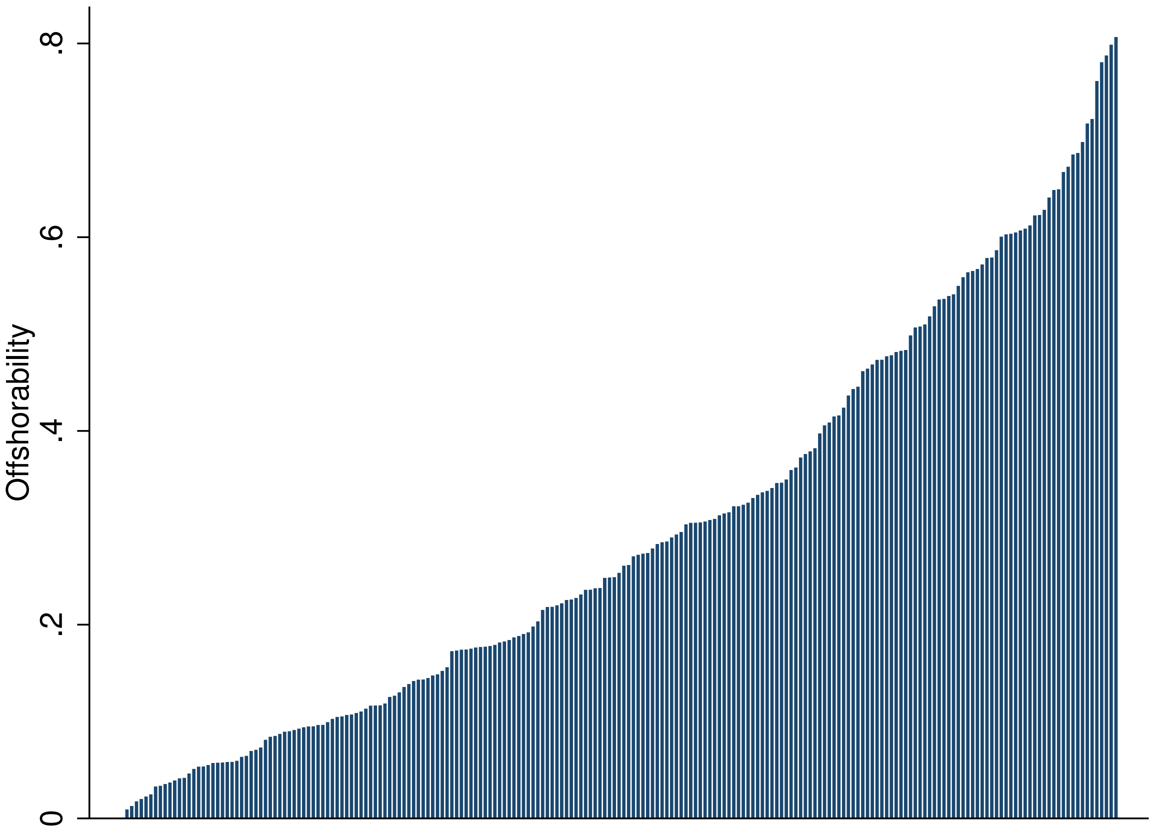
In practical terms, we have mapped the US SOC-based indicator into the German 3-digit KldB1988 classification applying a series of cross-walks (similar to Goos et al., 2014). Originally, the variable is measured on a 5-point scale, where 1 denotes occupations that are "not offshorable" and 5 denotes occupations that are "easily offshorable". After applying the various cross-walks, which sometimes involve a many-to-many mapping and therefore give rise to a weighted average, this clean 5-point scale is slightly blurred in the German occupational data. We therefore use the following operationalization of this measure. We convert the offshorability measure in a 0/1 dummy variable such that the top 25% (1988 employment-weighted) of occupations are coded as offshorable. While arguably arbitrary, this way of coding is both convenient and closely related to the existing literature. It is consistent with Blinder and Krueger (2013), who find that their various offshorability measures all lead to the conclusion that roughly 25% of US jobs are offshorable. Firpo et al. (2011), using their O*NET based offshorability measures, also use a top-quartile binary indicator in their empirical analysis.[30] As stated above, in terms of interpretation, the advantage of this approach is that, at the aggregate industry level, the offshorability corresponds to the share of offshorable jobs. We provide a detailed description of how we have constructed the offshorability measure in Appendix B.1.

Figure 4 depicts the variability in offshorability across 3-digit industries in our sample, while Table 8 in Appendix B.1 lists the industries with the highest and lowest offshorability scores,

[29]There are various alternative operationalizations of occupation-level offshorability indicators. Firpo et al. (2011) and Acemoglu and Autor (2011), among others, make use of the O*NET database, which contains job content descriptions for detailed US SOC occupations. In the German setting, Spitz-Oener (2006) was the first to use the IAB/BIBB survey data to construct the five task content measures proposed by Autor et al. (2003), using information about the respondents' job activities. These, however, were not directly designed to capture offshorability. Relying on the same data set, but using detailed information about the respondents' workplace tools, Becker et al. (2013) have constructed measures of non-routine and personally interactive task content, respectively, and they have shown that offshoring activities of German multinationals are associated with wage-bill shifts towards more non-routine and personally interactive tasks. Baumgarten et al. (2013) have used the same measures to analyze heterogeneous wage effects of offshoring in the German manufacturing sector. This brief list is a good illustration of David Autor's complaint that "[i]t is regrettably the case that there are almost as many distinct task classifications as there are papers in the task literature" (Autor, 2013, footnote 28). He therefore advocates for the use of standardized "off the shelf" measures.

[30]In a similar way, Autor and Dorn (2013) classify those occupations as routine-intensive that are in the top employment-weighted third of their continuous routine task-intensity measure in the start-of-sample period.

Figure 4: Variability in offshorability across 3-digit industries



Notes: Offshorability is measured by the share of offshorable jobs in the industry in West Germany in 1988, where offshorable jobs are defined as being in the (employment-weighted) top 25% of the Blinder-Krueger offshorability score in 1988.
Source: SIAB 1975–2014, own calculations.

respectively. It can be seen that the offshorability score ranges from 0 to 0.81, implying that in some industries up to 81% of jobs could potentially move abroad.

We also performed a few plausibility checks to make sure that this measure indeed captures what we aim to measure: the offshoring potential of different industries prior to the fall of the Iron Curtain. Results are presented in Table 1. Indeed, we find that it is positively and highly significantly related to the change in actual offshoring intensity, as measured based on the input-output indicators described above, in the aftermath of the fall of the Iron Curtain.[31] The correlation is weaker and not significant for the change in services offshoring, but as seen above, services offshoring only accounts for a small share in total offshoring activities. For the most comprehensive offshoring indicator, wide offshoring, variation in the offshorability measure explains reasonably high 17% of the variation in posterior offshoring growth. We also find that a larger share of offshorable

[31]As these input-output based offshoring indicators can only be constructed at the 2-digit industry level, these correlations are also at the 2-digit industry level while the subsequent empirical analysis is done at the 3-digit level.

Table 1: Pre-fall offshorability and changes in offshoring as well as displacement of offshorable jobs in 2-digit industries

	ΔOff. wide 1991–2007	ΔOff. narrow 1991–2007	ΔOff. material 1991–2007	ΔOff. services 1991–2007	ΔShare off. jobs 1988–2014
Offshorability	0.100***	0.062***	0.071**	0.020	−0.243***
	(0.030)	(0.023)	(0.030)	(0.012)	(0.066)
Observations	57	57	57	57	59
R squared	0.17	0.12	0.09	0.04	0.19

Notes: * p<0.10, ** p<0.05, *** p<0.01
Standard errors given in parentheses. Offshorability is measured by the share of offshorable occupations in the industry, where offshorable occupations are defined as being in the (employment-weighted) top 25% of the Blinder-Krueger offshorability score in 1988.

jobs in 1988 is strongly negatively related to the change in the share of offshorable jobs between 1988 and 2014, providing suggestive evidence that these types of occupations have increasingly been displaced after the fall of the Iron Curtain.

3.4 Results

Table 2 displays the estimation results pertaining to various variants of Equation (18). In these regressions, we consider the longest possible horizon and focus on long-run changes in log total employment between 1988 and 2014. The specification of the first column contains only the quadratic offshorability term, the second adds a manufacturing dummy, and the third and fourth add the full set of control variables. While all of these regressions make use of the entire set of 3-digit industries in the West German economy, the last column restricts attention to industries in the manufacturing sector.

Consistent with Proposition 1 of the theoretical model, we find, throughout these specifications, clear evidence for a hump-shaped relationship between the initial share of offshorable jobs in an industry and subsequent (long-run) employment growth, as the negative coefficient of the squared offshorability term reveals. The significance of this relationship rises as we add control variables, and it also holds if we restrict attention to the manufacturing sector.[32] Importantly, if we reestimate our richest specification, but only include the linear offshorability term – as done in the existing empirical literature – the resulting coefficient is small and insignificant (specification 4). Based on this result, we would erroneously conclude that offshoring does not matter at all for employment while, in fact, the relationship is simply non-monotonic.

[32] We also test more formally for the existence of a hump-shaped relationship applying the appropriate test of Lind and Mehlum (2010), which tests the null hypothesis of a monotone or U-shape relationship against the (one-sided) alternative of an inverse U-shaped relationship. For our richest (and preferred) specification (3), the p-value of the test is 0.003, implying statistical significance at all conventional levels. The null hypothesis of a monotone or U-shaped relationship has also to be rejected for specification (5), where we restrict attention to the manufacturing sector (p-value of 0.018).

Table 2: Offshorability and long-run employment growth at the 3-digit industry level

	(1) All	(2) All	(3) All	(4) All	(5) Manufacturing
	Dependent variable: Δ ln total employment 1988–2014				
Offshorability	1.171	3.993**	3.210***	−0.042	2.588**
	(1.359)	(1.737)	(1.132)	(0.383)	(1.075)
Offshorability squared	−2.854*	−4.961***	−4.255***		−2.972**
	(1.607)	(1.711)	(1.292)		(1.264)
Manufacturing (0/1)		−0.920***	−0.435**	−0.268	
		(0.300)	(0.215)	(0.220)	
Controls	No	No	Yes	Yes	Yes
Observations	219	219	219	219	103
R squared	0.05	0.20	0.50	0.48	0.52

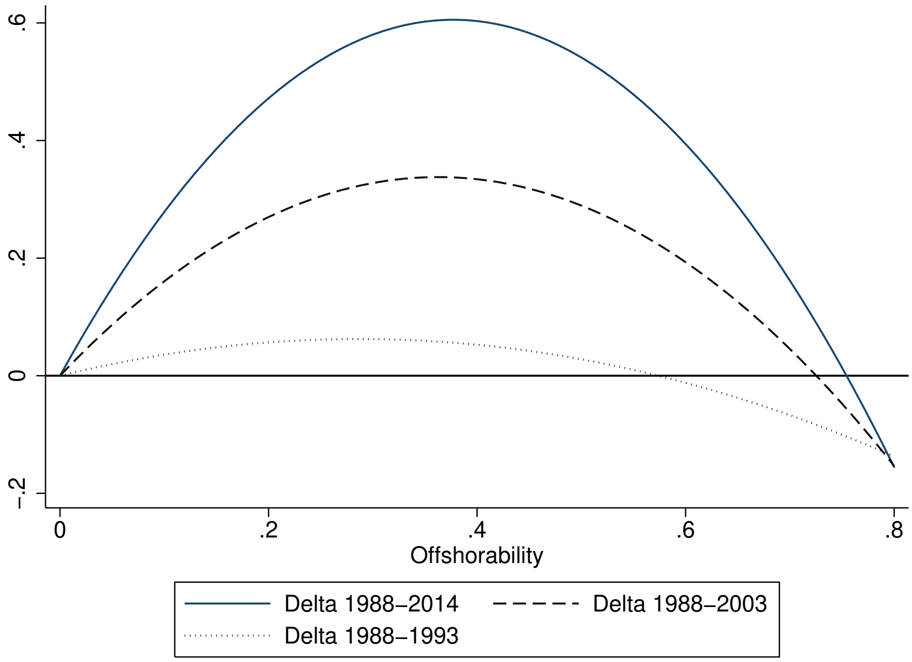
Notes: * p<0.10, ** p<0.05, *** p<0.01
Standard errors (given in parentheses) are clustered at the 2-digit industry level. Offshorability is measured by the share of offshorable jobs in the industry, where offshorable jobs are defined as being in the (employment-weighted) top 25% of the Blinder-Krueger offshorability score in 1988. Further controls (all measured in 1988): employment shares by age (5 groups); employment shares by education (5 groups); female employment share; foreign employment share; quadratic term of log total employment.

To aid the (quantitative) interpretation, we also graphically illustrate the quadratic relationship by plotting the predicted values resulting from the offshorability-related coefficients in specification (3) against the offshorability values in the sample (see the solid line in Figure 5). The maximum employment growth is reached at an offshorability value of 0.38 and amounts to 61 log percentage points. It turns negative at an offshorability value of 0.77, which is still within the range of observable values in the sample. Thus, there are indeed sizable differences in terms of long-run employment growth after the fall of the Iron Curtain across industries depending on their initial share of offshorable jobs.[33]

How does the relationship between ex-ante offshorability and posterior employment growth look like for different horizons? Instead of presenting the detailed regression tables, we directly jump to the graphical illustration, again making use of the regression results of the richest specification with all control variables (Figure 5). In addition to the already discussed results for $h = 26$ (i.e. 1988–2014), we show results for $h = 5$ (1988–1993) and $h = 15$ (1988–2003). It can be seen that the hump shape becomes more pronounced over longer horizons. In the short run, the hump shape is even hardly visible, reflecting the small and insignificant coefficients on both the linear and the squared

[33] The graph reflects *relative* differences in employment growth across industries with different ex-ante offshorability, but not their (predicted) *absolute* growth rates. Thus, one should not conclude that basically all industries gained employment between 1988 and 2014. The graph showing the same relationship, but evaluated at the sample means of the control variables, is displayed in Appendix B.3.

Figure 5: Offshorability and employment growth at the 3-digit industry level: different horizons



Notes: The figure depicts the relationship between the start-of-period offshorability measure and the change in log total employment between 1988 and different end years according to the regression specification (3). The graph reflects *relative* differences in employment growth across industries with different ex-ante offshorability, but not their (predicted) *absolute* growth rates.

offshorability term (not shown here). This is consistent with Proposition 2 of the theoretical model, according to which the general-equilibrium effects driving the hump increase with falling offshoring costs over time. In addition, it might also reflect that (i) offshoring did not take off immediately, but a couple of years after the fall of the Iron Curtain (as evidenced in Figure 3) and (ii) inter-industry worker (and capital) reallocation takes some time.

In sum, the empirical results provide strong support for the theoretical predictions that the relationship between the prospects for offshoring and employment growth at the industry level is not monotonic and becomes more pronounced over time. Industries in the medium range of offshorable tasks gain employment relative to industries both at the top and the bottom of offshorability.

3.5 Robustness checks

In this subsection, we subject our key finding of a non-monotone, hump-shaped relationship between ex-ante offshorability and subsequent industry-level employment growth to a series of robustness checks. We focus on our main specification (3) and the longest possible horizon of 26 years (1988–2014) for the dependent variable. Here, for the sake of space, we only explain the robustness checks briefly, while a detailed discussion is provided in Appendix B.4.

Different functional forms As a first robustness check, we consider different and more flexible functional forms of the offshorability term. In particular, we show that the hump shape also emerges if we include a cubic and a semi-parametric (piecewise-constant) function, respectively.

Alternative offshorability measures We also analyze to what extent our results hinge on the exact offshorability measure chosen. On the one hand, we check different alternative implementations of the Blinder and Krueger (2013) offshorability measure, i.e. we make the cut at the top 33% and the top 20% of occupations, respectively, and we consider a continuous, standardized measure with mean 0 and a standard deviation of 1. On the other hand, we also consider the offshorability measure proposed by Acemoglu and Autor (2011), which is based on various items of the O*NET database.[34] All specifications give rise to a hump shape, with slightly varying levels of statistical significance.

Additional control variables We address the potential concern that the relationship between employment growth and offshorability might in fact pick up other underlying factors, and hence, suffer from omitted variable bias. We address two specific concerns. First, the relationship might be driven by long-term (and pre-existing) trends which potentially could drive both offshorability in 1988 and subsequent employment growth. To tackle this concern, we include lagged employment growth (between 1978 and 1988) as an additional regressor. Second, one might be worried that our offshorability term might capture technological change rather than offshoring. To address this concern, we augment the specification with a routineness indicator which aims to capture the susceptibility to automation and computerization, the two key elements of technological change over the period of analysis. It is based on the measures proposed by Spitz-Oener (2006). The hump-shaped relationship between employment growth and offshorability remains robust to both of these amendments. In contrast, we cannot reject the null hypothesis of a monotone relationship between routineness and subsequent employment growth.

German reunification as a confounder? One additional potential concern for our analysis is that, with the fall of the Iron Curtain, West German firms not only obtained new opportunities to offshore production to nearby and lower-cost destinations, but also got access to the workforce from East Germany. To the extent that West German firms shifted parts of the production process to East Germany, this is not problematic for our empirical analysis as it also implies the same type of production fragmentation that we are interested in. However, at the same time, there were large migration flows from East Germans to West Germany (e.g. Burda, 1993; Burda and Hunt, 2001). If these internal migrants got employed in West German industries according to the same uneven distribution depending on the industry's offshorability, they might confound our offshoring-related effect. However, we argue that pure timing suggests that East-West migration should not affect

[34] For the Acemoglu and Autor (2011) measure, we consider three operationalizations: (i) the top 33% (1988 employment-weighted) of occupations are classified as offshorable; (ii) the top 25% (1988 employment-weighted) of occupations are classified as offshorable; (iii) a continuous, standardized measure with mean 0 and a standard deviation of 1 (across individuals in 1988).

our results as most of it happened before offshoring picked up and the characteristic hump shape emerged (see Appendix B.4.4 for details).

3.6 Extensions

In this subsection, we consider two extensions to our main empirical analysis. First, we analyze the importance of establishment entry and exit for the differential growth rates across industries. Second, we consider changes in industry wage premia as an alternative outcome variable.

3.6.1 The role of establishment entry and exit

We distinguish industry employment changes at the intensive and the extensive margin, respectively. By intensive margin, we refer to employment changes at continuing establishments which already existed in 1988.[35] In contrast, the extensive margin refers to employment changes brought about by entering and exiting establishments. To make both margins additively separable, we slightly modify the construction of the outcome variable. Instead of focusing on the change in log employment, we calculate growth rates as in the job-flow literature (Davis and Haltiwanger, 1992). That is, the total employment growth rate ($TEGR$) of industry j over time horizon h is calculated as

$$TEGR_{jh} = \frac{E_{j,1988+h} - E_{j,1988}}{\overline{E}_{jh}}, \tag{19}$$

with E denoting total employment and $\overline{E}_{jh} = 0.5 * (E_{j,1988+h} + E_{j,1988})$ measuring average employment at the start (1988) and the end (varying with horizon h) of the period of analysis. This measure is bound between -2 and 2 and thus less prone to outliers than if we just divide by start-of-period employment. The intensive margin is then defined as

$$IM_{jh} = \frac{E^{cont}_{j,1988+h} - E^{cont}_{j,1988}}{\overline{E}_{jh}}, \tag{20}$$

with the superscript *cont* indicating that we are restricting attention to continuing establishments, and the extensive margin as

$$EM_{jh} = \frac{E^{new}_{j,1988+h} - E^{exit}_{j,1988}}{\overline{E}_{jh}}, \tag{21}$$

with the superscript *new* (*exit*) indicating that we are summing over newly established (exiting) establishments. By summing employment over newly created and exiting establishments instead of simply counting their number, we implicitly take into account how much entrants and exiters contribute to overall employment changes at the industry level. Note that we count establishments switching industries towards the extensive margin, i.e. as exits in the previous industry and entries in the new industry.

[35] Our data set, which we describe below, has establishments (or plants) rather than firms as units of analysis.

Table 3: Employment growth at the establishment intensive and extensive margin

	(1) TEGR	(2) IM	(3) EM
Offshorability	1.6630**	0.0847	1.5784**
	(0.6629)	(0.2821)	(0.6485)
Offshorability squared	−2.3515***	−0.0605	−2.2911***
	(0.7389)	(0.3841)	(0.7127)
Controls	Yes	Yes	Yes
Observations	209	209	209
R squared	0.529	0.241	0.511

Notes: * p<0.10, ** p<0.05, *** p<0.01
Standard errors (given in parentheses) are clustered at the 2-digit industry level. TEGR: Total employment growth rate, calculated according to Equation (19). IM: Intensive margin (cf. Equation 20). EM: Extensive margin (cf. Equation 21). Offshorability is measured by the share of offshorable jobs in the industry, where offshorable jobs are defined as being in the (employment-weighted) top 25% of the Blinder-Krueger offshorability score in 1988. Further controls included as described in Table 2.

To construct these measures, we use a different data set, the Establishment History Panel.[36] Based on the same data source of administrative social security records, this data set is a 50% random sample of establishments that had at least one employee liable to social security on the reference date (30th of June of each year). All the individual-level data have been aggregated to the establishment level.[37]

We then run the same regression model as in our preferred specification, but with our alternative outcome variables. We merge our industry-level offshorability indicators from our main data set and reconstruct the control variables as well as possible from the Establishment History Panel. Due to data confidentiality issues, we lose information on 10 (out of 219) 3-digit industries.

Results are displayed in Table 3. For comparison, the first column displays the results for total employment growth. It is comforting that, despite the different data set, the slightly modified dependent variable, and the fewer industry observations, the offshorability-related results are qualitatively very similar. The hump shape again shows up very clearly. Results on the intensive and the

[36] We use the weakly anonymous Establishment History Panel (years 1975–2014). See Schmucker et al. (2016) for a detailed description of the data.

[37] Due to their unique establishment ID, establishments can be followed over time. Establishment entry and exit can, in principle, be identified through new and exiting establishment IDs, respectively. The caveat is, though, that these IDs might occasionally also change if there is a change in ownership, a change in the legal form, or similar. To distinguish true from false entries and exits, we use additional indicators developed by Hethey-Maier and Schmieder (2013) based on worker flows. Specifically, they consider the case that a large fraction of workers "moves" from an exiting establishment ID to a newly appearing establishment ID, while also accounting for most of the workers of this new establishment ID, to signal an ID change of a continuing establishment. We clean the data from these (likely) false exits and entries by assigning the predecessor establishment ID to the succeeding establishment.

extensive margin are shown in columns (2) and (3), respectively. Strikingly, the offshorability-related hump is almost entirely due to the extensive margin, underscoring the importance of establishment entry and exit for these differential growth rates across industries. Note that this pattern of the extensive margin is also broadly consistent with our theoretical model.[38]

3.6.2 Wages as an alternative outcome variable

Since the prediction derived from our theoretical model refers to (changes in) total employment across industries, we have focused on this outcome variable in the empirical analysis. To keep the theoretical model as parsimonious as possible and in line with much of the related literature (e.g. Grossman and Rossi-Hansberg, 2008), we have abstracted from any frictions in the labor market. Thus, there is no unemployment, and there are no wage differences across industries. However, one could also think of settings where not all the adjustments take place via changes in total employment. For example, in the presence of industry-specific unions or with imperfect inter-industry mobility, the offshoring shock might also lead to differential wage reactions across industries. In fact, many empirical studies have focused on wages as an outcome variable (e.g. Baumgarten et al., 2013; Ebenstein et al., 2014; Hummels et al., 2014).

To check whether we obtain a similar hump-shaped pattern for wages, we run the same type of regressions as before, but focus on changes in industry wage premia as our outcome variable. Following the approach adopted in, e.g., Goldberg and Pavcnik (2005), we calculate these industry wage premia in a first step from the following year-specific Mincerian wage regressions:

$$\ln w_{ijt} = \gamma_{jt} + X'_{ijt}\beta_t + u_{ijt}, \tag{22}$$

where i denotes the individual, j the 3-digit industry, and t the year. w_{ijt} is the daily wage, the wage measure included in the social security data.[39] To make the sample as homogeneous as possible and to abstract from compositional changes due to increased female labor force participation and increased part-time employment, we restrict the sample to male full-time workers in regular employment, aged 18 to 65. The estimated coefficient of the industry dummies, $\hat{\gamma}_{jt}$, is our measure of the industry wage premium. More precisely, we again follow Goldberg and Pavcnik (2005) and apply the deviation contrast form to these coefficients such that they represent log deviations from the employment-weighted grand mean rather than from some arbitrary base category. We

[38]The theoretical counterpart for (the numerator of) Equation (21) is given by

$$EM = \begin{cases} [n(z) - n_{aut}](1-z)y(z) & \text{if} \quad z \geq \frac{1}{2} \\ [n(z) - n_{aut}]y_{aut} & \text{if} \quad z < \frac{1}{2} \end{cases}.$$

This function also yields a hump-shaped pattern. It equals 0 for $z = \frac{1}{2}$ (since $n(\frac{1}{2}) = n_{aut}$) and $z = 1$, whereas it is positive (negative) for $\frac{1}{2} < z < 1$ ($z < \frac{1}{2}$).

[39]The wage information given in the social security data is right-censored at the contribution ceiling to the social security system. In the sample at hand, between 10 and 14% of the wage observations are top-coded each year. In order not to bias the regression results, we replace censored wages with imputed wages, applying the imputation procedure pioneered by Gartner (2005) and applied in many other papers such as Dustmann et al. (2009), Card et al. (2013), etc.

Table 4: Offshorability and long-run changes in 3-digit industry wage premia

	(1)	(2)	(3)	(4)
	Dependent variable: Δ industry wage premium 1988–2014			
Offshorability	0.6698**	0.5275**	0.3693*	0.3066
	(0.2730)	(0.2587)	(0.2102)	(0.1877)
Offshorability squared	−0.7811**	−0.6190*	−0.4383	−0.3908
	(0.3731)	(0.3502)	(0.2830)	(0.2554)
Controls	Yes	Yes	Yes	Yes
Observations	218	218	218	218
R squared	0.35	0.34	0.35	0.32
Controls in wage premia regressions				
Sociodemographics	No	Yes	Yes	Yes
Federal state dummies	No	Yes	Yes	Yes
Occupation dummies	No	No	Yes	Yes
Establishment size	No	No	No	Yes

Notes: * p<0.10, ** p<0.05, *** p<0.01
Standard errors (given in parentheses) are clustered at the 2-digit industry level. Industry wage premia have been estimated according to Equation (22) on samples of full-time employed male workers in regular employment, aged 18 to 65. The columns differ in the set of control variables included in the regressions of Equation (22) as listed in the lower part of the table. Sociodemographics: controls for education (five categories), age (five categories), and nationality. Establishment size: quadratic term of log establishment total employment. In the industry-level regression, offshorability is measured by the share of offshorable jobs in the industry, where offshorable jobs are defined as being in the (employment-weighted) top 25% of the Blinder-Krueger offshorability score in 1988. Further controls included as described in Table 2.

estimate different variants of Equation (22), where we start from a baseline specification without any controls and then sequentially add controls for age, education, nationality, the region (at the federal state level), the occupation, and establishment size such that worker-level (and employer-level) heterogeneity is accounted for.

Then, in the second step, changes in the estimated wage premia are used as the dependent variable in our industry-level regressions according to Equation (18), where we focus on the richest specification with all the relevant controls and the longest possible horizon from 1988 to 2014. Results are displayed in Table 4.

As can be seen, we again obtain the hump-shaped pattern with respect to ex-ante offshorability. Both the magnitudes and the levels of statistical significance are reduced when we use the (arguably more appropriate) wage measure that has been purged from worker-level heterogeneity.[40]

[40] While the coefficient on the squared term is not statistically significant in specifications (3) and (4), the p-values of the formal tests of Lind and Mehlum (2010) amount to 0.088 and 0.082, respectively, thus weakly rejecting the null

Nevertheless, the results lend some support to the notion that non-monotonic effects of offshoring across industries are relevant for a variety of labor market outcomes.

4 Implications

In this section, we describe the broader implications of our results for both empirical and theoretical studies of offshoring. In particular, we discuss their importance for the empirical identification of the labor market effects of offshoring in general equilibrium. Moreover, we highlight theoretical implications specific to our model that have so far been neglected in the literature.

4.1 Empirical identification of the labor market effects of offshoring

On the empirical side, our results provide a cautionary tale about using industry-level variation to identify the (labor market) effects of offshoring. In particular, the standard reduced-form approach of inserting a linear offshoring or offshorability term in the regression may lead to misguided conclusions if these industries are connected in general equilibrium.

Technically, one can think of these studies adopting a difference-in-differences approach, with offshoring or offshorability as the continuous treatment variable. Thus, industries with greater treatment doses are compared to industries with smaller treatment doses. Like other treatment effect estimators, one assumption needed for identification is the so-called Stable Unit Treatment Value Assumption (SUTVA), according to which there is no interference between treatment and control observations. If general-equilibrium effects such as the ones described in our paper are active, this assumption is violated. Then, essentially, also the supposed "control" observations with smaller offshorability values are affected by increased offshoring in other industries. Thus, the effects of offshoring may show up where they are least expected.

What sets our analysis apart is that we have derived our central prediction of a non-monotonic labor demand effect across industries in response to a positive offshoring shock in a framework that explicitly accounts for these general-equilibrium feedback effects. The empirical results lend support to this prediction.

A natural follow-up question is under which conditions these effects are relevant and, hence, the standard partial-equilibrium approach is more likely to lead to distorted results. Our general-equilibrium channels hinge on labor and capital mobility across industries. Arguably, these are more relevant in the long run than in the short run. Also in the empirics, we have seen that the predicted hump shape only shows up over pretty long horizons. Thus, studies focusing on short-term reactions to an offshoring shock are probably less affected than studies focusing on longer-term outcomes.

In this paper, we have focused on industry-level heterogeneity in the prospects for offshoring and the resulting labor market effects across industries. With the focus on industry aggregates as the outcome variable, in terms of the empirical analysis, our study is closest to the early papers on the labor market effects of offshoring such as Amiti and Wei (2005). However, we also speak to a

hypothesis of a monotone or U-shaped relationship against the alternative of an inverse U-shaped relationship.

large empirical literature that uses individual-level data, but still relies on industry-level variation in offshoring to identify the effects.

We do not, however, address any effects within industries across heterogeneous employers. Those have recently been explored in theoretical papers such as Egger et al. (2015) and empirical papers such as Hummels et al. (2014). Still, similar mechanisms to the ones that we outline in this paper are likely to play a role in these settings, as well. For example, Hummels et al. (2014) essentially compare workers employed at firms that experience larger changes in offshoring to workers employed at firms experiencing smaller changes in offshoring to learn about the offshoring-related wage effects. However, to the extent that these firms are connected in general equilibrium, e.g. because they (at least partially) rely on the same labor market or compete in the same product market, this comparison under the implicit assumption of monotonicity might not necessarily represent the true effect of offshoring. Again, it could be the case that firms not offshoring at all are negatively affected by offshoring activities taking place elsewhere, potentially giving rise to non-monotonic effects.

4.2 Effect of mobile capital on the labor market

In our theoretical model, we allow capital to be mobile across industries. Here, we argue that the opportunity to reinvest capital formalizes a new channel through which offshoring may affect labor market outcomes. Since returns to capital are higher in offshoring-intensive industries, our model predicts capital reallocation towards those industries. Hence, firms exit predominately domestic industries and enter more offshoring-oriented industries. This reallocation of capital implies that many jobs break away in industries where a large share of tasks is produced domestically, and only few new jobs are created in industries with a large fraction of offshore production. For domestic workers, this has two implications. Firstly, workers need to switch industries to find a new job (this aspect is discussed in detail in the next subsection). Secondly, since firm exit in non-offshoring-intensive industries destroys more jobs than are created by firm entry in offshoring-intensive industries, domestic wages have to adjust to ensure an equilibrium at the labor market. We argue that this so far unexplored channel of inter-industry reallocation of capital mitigates the productivity effect of offshoring in a long-run equilibrium. To prove this result formally, we compare the domestic wage rate in Equation (7), where the the allocation of capital is fixed, to the wage in Equation (15), where capital is mobile.[41] The difference in wages $\Delta_w = w_s - w$ is given by

$$\Delta_w = \frac{3b\left(\frac{L^*}{\tau} - L\right)}{K} > 0 \tag{23}$$

and widens as the cost savings from offshoring become larger:

$$\frac{\partial \Delta_w}{\partial \tau} = -\frac{3bL^*}{K\tau^2} < 0. \tag{24}$$

[41] It is important to note that wages should be interpreted as "real at the margin" (cf. Neary, 2016), and therefore, we cannot derive any welfare implications by simply interpreting the level of wages. However, we can compare changes in wages between the two equilibria (with and without capital mobility).

While falling offshoring costs increase domestic wages in a short-run equilibrium without capital mobility (through the productivity effect), there is a counteracting force in an equilibrium where firms are mobile across industries. Falling offshoring costs imply larger returns to capital in offshoring-intensive industries and, hence, more capital movements towards those industries. This mitigates the productivity effect and widens the gap between short-run and long-run wages since firms reallocate towards industries where only a small share of production is carried out domestically. Hence, by ignoring inter-industry reallocations, existing models exaggerate the productivity effect of offshoring on domestic labor markets.

4.3 Adjustment dynamics and costs

The results of our analysis imply a substantial inter-industry worker reallocation from industries that are characterized by either a very low or a very high offshorability to industries with an intermediate share of offshorable tasks. For workers in those vulnerable industries, this means that many of them have to switch industries after an offshoring shock occurs. While modeling switching costs across industries is beyond the scope of our paper, inter-industry reallocations of workers may be associated with high moving costs in reality. These costs could include spells of unemployment, search costs, or reeducation. Artuç et al. (2010) document large gross flows of workers across industries and analyze the costs faced by workers that have to switch industries in response to import competition. Their estimates for moving costs from one industry of the economy to another can be up to several times the average annual wage rate. Similar to that paper, Dix-Carneiro (2014) allows workers to accumulate sector-specific capital. Hence, workers possess comparative advantages across sectors that cause barriers of inter-sectoral mobility. The author documents median costs of mobility which range from 1.4 to 2.7 times annual average wages. These studies document high switching costs, which – following our paper – could also become relevant for workers in industries with low offshoring activities.

5 Conclusion

In this paper, we have analyzed both theoretically and empirically the effect of offshoring on labor demand across industries that differ in their ability to shift parts of the production process abroad. Moving beyond one-sector or two-sector models, we have instead set up a multi-industry framework with general-equilibrium feedback effects across industries to closely match the common empirical set-up. A key new insight deriving from this theoretical framework is that (negative) labor market effects arise even in industries where no tasks can be produced offshore, which results from higher domestic production costs and the reinvestment of capital towards industries which experience greater cost savings from offshoring. These so far unexplored inter-industry feedback effects generate a non-monotonic relation between offshorability and labor demand across industries. In the empirical analysis, we find strong empirical support for the hump shape in the change of employment (and wages) across industries. Thus, the findings of this paper question the standard empirical practice of simply including a linear offshoring term in the regression, at least in settings where general-equilibrium effects across industries are likely to be relevant, such as over longer horizons.

From a policy perspective, our results suggest that one should reevaluate trade adjustment assistance programs such as the US TAA Program. These are specifically targeted at workers that are directly affected by trade-related circumstances (e.g. increase in imports or a shift in operations abroad).[42] However, if due to general-equilibrium effects, those workers that at first sight are not exposed to any offshoring threats in fact bear a large part of the adjustment burden, this suggests that policy makers should rather strengthen general, non-targeted adjustment assistance programs.

While we think that this paper provides a useful tool to study the effects of offshoring in an empirically relevant setting, it is clear that the parsimonious structure of the theoretical model lowers the ability to capture other important features of the data. For instance, in our setting we ignore intra-industry heterogeneity among firms as well as frictions in the ability of factors to migrate between industries. Going into this direction would therefore be a worthwhile task for future research.

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A Theoretical Appendix

To substantiate our findings from the main framework, we discuss the robustness of the labor reallocation effects, especially the hump shape in labor demand across heterogeneous industries. In particular, we show that our main results are robust to the introduction of fixed costs of offshoring, a Cobb-Douglas technology, as well as a more general production technology, where offshoring is not linearly increasing in z.

A.1 Fixed costs of offshoring

In this subsection, we introduce fixed costs of offshoring. To be more specific, firms have to invest F units of foreign labor to relocate production abroad and organize international fragmentation. This introduces a cutoff industry $\widetilde{z}$, at which firms are indifferent between domestic and foreign production, i.e. $\pi_d(\widetilde{z}) = \pi_o(\widetilde{z})$, and thus

$$b\left(\frac{a' - w}{b[n(\widetilde{z}) + 1]}\right)^2 = b\left(\frac{a' - \widetilde{z}w^*\tau - (1-\widetilde{z})w}{b[n(\widetilde{z}) + 1]}\right)^2 - w^*F. \tag{25}$$

If fixed offshoring costs are sufficiently high, industries $z < \widetilde{z}$ will produce purely domestically and are therefore fully symmetric. With fixed offshoring costs, the equilibrium is determined by Equation (25) together with the domestic and foreign labor market clearing conditions

$$L = \widetilde{z}n(\widetilde{z})y(\widetilde{z}) + \int_{\widetilde{z}}^{1}(1-z)n(z)y(z)dz \quad \text{and} \quad L^* = \tau\int_{\widetilde{z}}^{1} zn(z)y(z)dz + F\int_{\widetilde{z}}^{1} n(z)dz, \tag{26}$$

the capital market clearing condition $K = \int_0^1 n(z)dz$, and $n(z)$ from the no-arbitrage condition $\pi(z) = \pi = \pi(0)$:

$$n(z) = \frac{[a' - zw^*\tau - (1-z)w]n(\widetilde{z}) + (z - \widetilde{z})(w - w^*\tau)}{a' - \widetilde{z}w^*\tau - (1-\widetilde{z})w}. \tag{27}$$

Instead of solving this non-linear system of equations, we present numerical solutions in Table 5, which we use to plot industry-specific labor demand $L(z) = (1-z)n(z)y(z)$ in Figure 6. From inspection of this figure, we conclude that the hump shape in labor demand across heterogeneous industries prevails even after introducing fixed offshoring costs.

Table 5: Equilibrium values for different variable offshoring costs

τ	w	w^*	w/w^*	$n(0)$	$\widetilde{z}$
2	390.81	192.08	2.03	4.47	0.41
1.5	391.47	253.34	1.55	3.64	0.24
1.1	395.29	337.25	1.17	1.20	0.06

Notes: We use the following parameter values $a = 20$; $L = 5$; $L^* = 10$; $K = 5$; $b = 1$; $F = 0.01$.

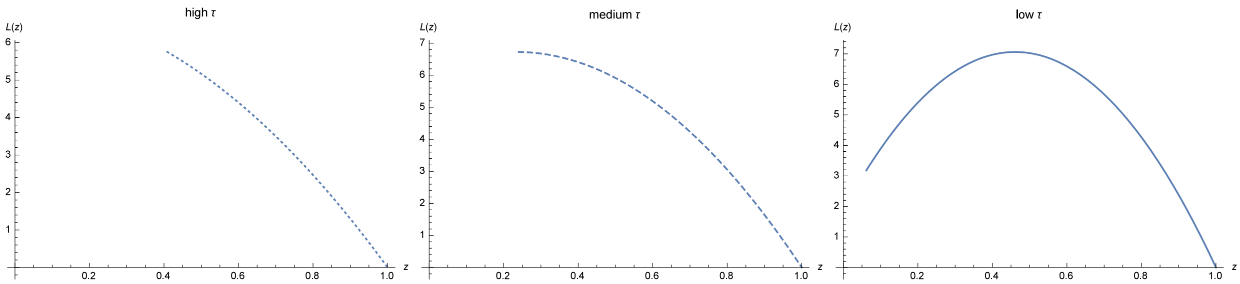


Figure 6: Industry-specific employment for different offshoring costs

A.2 Cobb-Douglas production technology

In this subsection, we show that the main results do not hinge on the specific technology we impose in the main text. Specifically, we introduce a Cobb-Douglas technology and show that the labor market effects of offshoring are robust to this specification. Suppose unit production costs in industry z are given by

$$c(z) = (w^*\tau)^z w^{1-z} = w\kappa^z, \tag{28}$$

where $\kappa \equiv w^*\tau/w$ denotes the cost savings from offshoring.[43] The equilibrium is then determined by the domestic and foreign labor market clearing conditions

$$bL = \int_0^1 (1-z)\frac{n(z)\,(a' - w\kappa^z)\,\kappa^z}{n(z)+1}dz \quad \text{and} \quad bL^* = \tau\int_0^1 z\frac{n(z)\,(a' - w\kappa^z)\,\kappa^{z-1}}{n(z)+1}dz, \tag{29}$$

the capital market clearing condition $K = \int_0^1 n(z)dz$, and $n(z)$ from the no-arbitrage condition $\pi(z) = \pi = \pi(0)$:

$$n(z) = \frac{(a' - w\kappa^z)[n(0)+1] - (a' - w)}{a' - w}. \tag{30}$$

Again, we solve the system of equations numerically and use the solutions presented in Table 6 to plot industry-specific labor demand $L(z) = (1-z)n(z)y(z)\kappa^z$. From inspection of Figure 7, we conclude that the hump shape in labor demand across heterogeneous industries prevails even with a Cobb-Douglas technology that allows for substitution among domestic and foreign workers.

[43]This cost function arises from solving a firm's cost minimization problem when output is produced according to a Cobb-Douglas technology with $y(z) = [l_o/z]^z[l_n/(1-z)]^{1-z}$, where l_o is labor input in the offshore location and l_n denotes domestic labor input.

Table 6: Equilibrium values for different variable offshoring costs

τ	w	w^*	w/w^*	$n(0)$
2	388.04	194.92	1.99	4.96
1.5	390.81	255.8	1.53	2.92
1.2	393.54	314.67	1.25	1.41

Notes: We use the following parameter values $a = 20$; $L = 5$; $L^* = 10$; $K = 5$; $b = 1$.

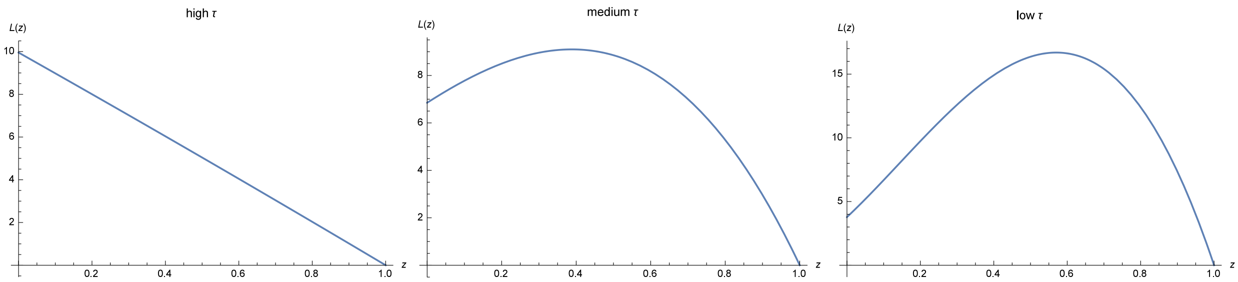


Figure 7: Industry-specific employment for different offshoring costs

A.3 More general production technology

Finally, we show that the hump shape in labor demand across industries is robust to a more general production technology, in which the share of offshorable tasks is not linearly increasing in the industry index z. To be more specific, we assume that unit production costs are given by

$$c(z) = \gamma_0 z^{\gamma_1} w^* \tau + (1 - \gamma_0 z^{\gamma_1}) w, \tag{31}$$

where γ_0 reduces the share of offshorable tasks to a maximum of $0 < \gamma_0 \leq 1$, and γ_1 is a shape parameter that affects differences across industries, with $0 < \gamma_1 < \infty$.[44] By allowing for this more flexible technology with $\gamma_0 < 1$, differences between the short-run and the long-run labor demand arise, and we present the solution to both cases for completeness in the following:

Short-run equilibrium Using the domestic labor market clearing condition $L = \int_0^1 L(z)dz$ with $L(z) = (1 - \gamma_0 z^{\gamma_1})ny(z)$ and the foreign labor market clearing condition $L^* = \tau \int_0^1 \gamma_0 z^{\gamma_1} ny(z)dz$ allows us to compute wages in the short run as

$$w_s = a' - \left(\frac{1+\gamma_1}{\gamma_1}\right)^2 \frac{n+1}{n} bL + \frac{1+\gamma_1}{\gamma_0\gamma_1^2} \left[1 + 2\gamma_1 - \gamma_0(1+\gamma_1)\right] \frac{n+1}{n} \frac{bL^*}{\tau} \quad \text{and} \tag{32}$$

$$\begin{aligned} w_s^*\tau = a' &+ \frac{1+\gamma_1}{\gamma_0\gamma_1^2} \left[1 + 2\gamma_1 - \gamma_0(1+\gamma_1)\right] \frac{n+1}{n} bL \\ &- \frac{1+\gamma_1}{\gamma_0^2\gamma_1^2} \left[(1-\gamma_0)(3-\gamma_0)\gamma_1 + (1-\gamma_0)^2 + 2\gamma_1^2\right] \frac{n+1}{n} \frac{bL^*}{\tau}. \end{aligned} \tag{33}$$

[44]Nota bene, with $\gamma_0 = \gamma_1 = 1$ we end up with the unit production costs from the main text.

Hence, industry-specific labor demand in the short run[45] is given by

$$L_s(z) = (1-\gamma_0 z^{\gamma_1})\frac{(1+\gamma_1)(1+2\gamma_1)}{\gamma_1^2}\left[\left(L+\frac{L^*}{\tau}\right)\left(\frac{1+\gamma_1}{1+2\gamma_1}-\gamma_0 z^{\gamma_1}\right)-\frac{L^*}{\tau}\frac{1-z^{\gamma_1}(1+\gamma_1)}{\gamma_0}\right]. \tag{34}$$

Long-run equilibrium To solve for the long-run equilibrium, we can first compute the number of firms as

$$n(z) = \frac{(a'-w)n(0)+\gamma_0 z^{\gamma_1}(w-w^*\tau)(n(0)+1)}{a'-w}. \tag{35}$$

Substituting into $K = \int_0^1 n(z)dz$ entails

$$n(0) = \frac{(1+\gamma_1)(a'-w)K-\gamma_0(w-w^*\tau)}{(1+\gamma_1)(a'-w)+\gamma_0(w-w^*\tau)}. \tag{36}$$

Substituting into the domestic and foreign labor market clearing conditions (see above) allows us to derive equilibrium wages

$$w = a' - \frac{\gamma_1^2+(1+\gamma_1)^2K}{\gamma_1^2K}bL + \frac{(1+\gamma_1)[1+2\gamma_1-\gamma_0(1+\gamma_1)]K-\gamma_0\gamma_1^2}{\gamma_0\gamma_1^2K}\frac{bL^*}{\tau} \quad \text{and} \tag{37}$$

$$\begin{aligned} w^*\tau = a' &- \frac{(1+\gamma_1)[(1-\gamma_0)(3-\gamma_0)\gamma_1+(1-\gamma_0)^2+2\gamma_1^2]K+\gamma_0^2\gamma_1^2}{\gamma_0^2\gamma_1^2K}\frac{bL^*}{\tau} \\ &+ \frac{\gamma_0(1+\gamma_1)[1+2\gamma_1-\gamma_0(1+\gamma_1)]K-\gamma_0^2\gamma_1^2}{\gamma_0^2\gamma_1^2K}bL. \end{aligned} \tag{38}$$

Finally, we derive labor demand across industries:

$$\begin{aligned} L(z) = &(1-\gamma_0 z^{\gamma_1})\frac{1+\gamma_1}{\gamma_0\gamma_1^2} * \\ &\left\{\gamma_0\left[1+\gamma_1-(1+2\gamma_1)z^{\gamma_1}\right]L-\left[1+2\gamma_1-\gamma_0(1+\gamma_1)-(1+2\gamma_1)(1-\gamma_0+\gamma_1)z^{\gamma_1}\right]\frac{L^*}{\tau}\right\} \end{aligned} \tag{39}$$

Again, we solve the system of equations numerically and use the solutions presented in Table 7 to plot industry-specific labor demand. From inspection of Figure 8, we conclude that the hump shape in labor demand across heterogeneous industries prevails even with a more general production technology.

[45] Focusing on $w > w^*\tau$ and $L(0) > 0$ thereby requires $\frac{\gamma_0}{1-\gamma_0+\gamma_1}L \leq \frac{L^*}{\tau} \leq \frac{\gamma_0(1+\gamma_1)}{1+2\gamma_1-\gamma_0(1+\gamma_1)}L$.

Table 7: Equilibrium values for different values for γ_0

γ_0	w	w^*	w/w^*	$n(0)$
1	195.24	87.90	2.22	4.44
0.9	196.53	84.58	2.32	2.96
0.8	198.15	79.63	2.49	1.11

Notes: We use parameter values $a = 200$; $L = 10$; $L^* = 15$; $K = 10$; $b = 0.5$; $\tau = 2$; $\gamma_1 = 3$.

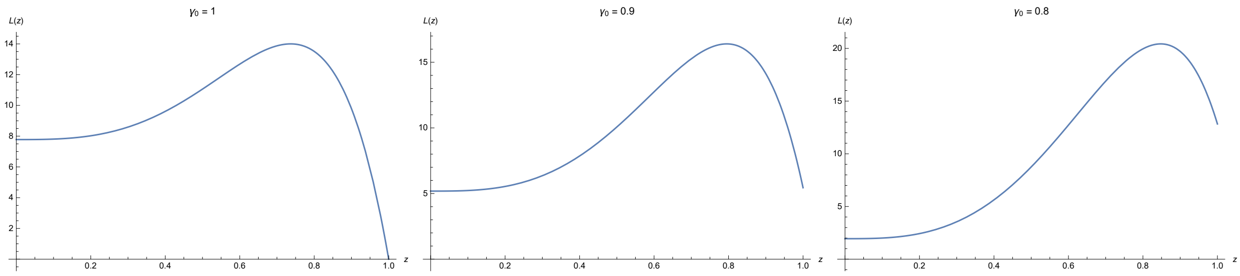


Figure 8: Industry-specific employment for different values of γ_0.

B Empirical Appendix

B.1 Data Appendix

Our preferred offshorability measure is taken from Blinder and Krueger (2013). We use their preferred indicator based on professional coders' assessment of whether the nature of the job "allows the work to be moved overseas in principle" (Blinder and Krueger, 2013, p. S99). This measure was developed as part of the Princeton Data Improvement Initiative (PDII). In the original data, the measure is available at the 6-digit occupational level following the US SOC 2000 classification.[46] To map this measure into the German KldB 1988 classification, which is used in the German employment data, we apply a series of cross-walks. First, we apply the crosswalk provided by the Bureau of Labor Statistics (BLS) from the 6-digit SOC 2000 to the more recent 6-digit SOC 2010 classification. In case that the mapping is not unique, we assign a weighted average of the offshorability measure to the new classification, using 2009 US labor supply weights. We then map the data into the international 4-digit ISCO 2008 classification, using the official crosswalk provided by the BLS and 2014 US labor supply weights.[47] Next, we apply the crosswalk provided by the German Federal Employment Agency from the 4-digit ISCO 2008 to the German 5-digit KldB 2010 classification, making use of 2014 labor supply weights. Finally, we map the data from the 5-digit KldB 2010 classification to the 3-digit KldB 1988 classification, again using the crosswalk provided by the German Federal Employment Agency and 2014 German labor supply weights. With this

[46]To be precise, the data are at the individual level, but generally, the same offshorability value is shared by individuals in the same 6-digit classification. In the few cases where different values were assigned to the same occupation, we chose the modal value. Using the mean value instead reproduces the results almost exactly.

[47]We have to use labor supply weights from varying years due to the changes in the occupational classification over time, which limit the availability of the required employment data.

approach, we are able to assign Blinder and Krueger (2013) offshorability values to 248 out of 335 3-digit KldB 1988 occupations in our data. We miss the remaining 87 occupations because (i) some of them are simply not mapped into by the crosswalks (-72 occupations) and (ii) the Blinder and Krueger (2013) offshorability measure is not available for all US SCOC occupations to start with (-15 occupations). We impute the offshorability value for the remaining occupations by assigning the weighted average of the next highest level of occupational aggregation, using 1988 labor supply weights.[48] Note that, while the number of occupations with imputed Blinder and Krueger (2013) offshorability scores seems rather high, they do only account for 12% of employment in 1988 West Germany.

Admittedly, this approach of assigning offshorability measures to the German 3-digit KldB 1988 occupations is prone to several sources of measurement error. First, the professional coders that assigned the scores probably did so with some margin of error to start with. Second, these offshorability scores were originally assigned to US occupations, yet we use them for German occupations. Thus, the assumption is that the work content of German occupations is similar to the one of their US counterparts. Third, they are constructed based on job content descriptions in the 2000s, yet we use them to characterize offshorability as of 1988. Clearly, job activities have also changed within occupations in that time span. However, we will mostly rely on an ordinal ranking of occupations so that the assumption is that occupations with a relatively high offshorability in the 2000s were also the ones with a relatively high (if potentially higher in absolute terms) offshorability in 1988. Fourth, we need to impute missing offshorability scores for a fraction of the German occupations. To the extent that the offshorability variable does indeed contain classical (random) measurement error, our regression results would be affected by attenuation bias. Note, however, that, despite the potential limitations of our approach, our offshorability variable has a reasonably high predictive power regarding the actual subsequent change in offshoring activities at the industry level. Moreover, we obtain offshorability scores at a very disaggregate occupational level, giving us substantial variation that we can exploit in our empirical analysis.

[48]The next-highest level of aggregation of the KldB 1988 classification comprises 86 occupational groups at the 2-digit level, followed by 33 occupational sections, and, finally, 6 broad occupational areas.

Table 8: Top 10 3-digit industries with highest and lowest offshorability in 1988 West Germany

Top 10 industries with highest offshorability	
Manufacture of footwear	0.81
Insurance and pension funding, except compulsory social security	0.80
Dressing and dyeing of fur; manufacture of articles of fur	0.79
Tanning and dressing of leather	0.78
Manufacture of leather clothes	0.76
Manufacture of ceramic tiles and flags	0.72
Preparation and spinning of textile fibres	0.72
Manufacture of non-refractory ceramic goods other than for construction purposes; manufacture of refractory ceramic products	0.70
Manufacture of luggage, handbags and the like, saddlery and harness	0.69
Activities auxiliary to insurance and pension funding	0.69

Top 10 industries with lowest offshorability	
Retail sale of pharmaceutical and medical goods, cosmetic and toilet articles	0.04
Telecommunications	0.03
Fishing, operation of fish hatcheries and fish farms; service activities incidental to fishing	0.03
Mining of chemical and fertilizer minerals	0.02
Post and courier activities	0.02
Camping sites and other provision of short-stay accommodation	0.02
Forestry, logging and related service activities	0.02
Primary education	0.01
Bars	0.01
Mining of iron ores	0.00

Notes: Offshorability is measured by the share of offshorable occupations in the industry, where offshorable occupations are defined as being in the (employment-weighted) top 25% of the Blinder-Krueger offshorability score in 1988.
Notes: SIAB 1975–2014, own calculations.

B.2 Summary statistics

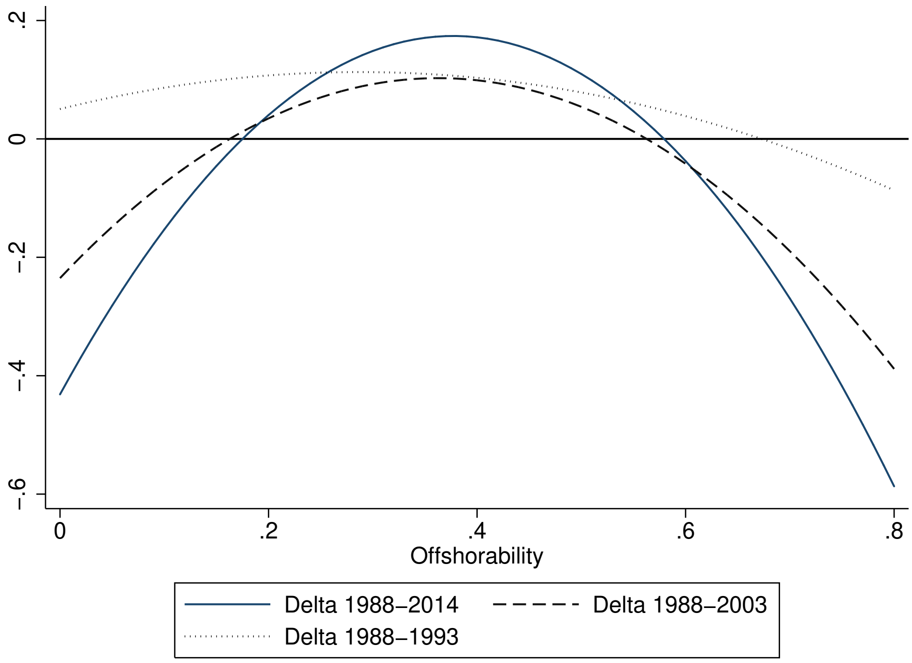
Table 9: Summary statistics

	Mean	Std. dev.
Δ ln total employment 1988–1993	0.08	0.29
Δ ln total employment 1988–2003	−0.02	0.73
Δ ln total employment 1988–2014	−0.04	0.92
Blinder-Krueger top 25% offshorability score	0.29	0.21
Manufacturing (0/1)	0.47	0.50
Share age: 26–35	0.27	0.06
Share age: 36–45	0.23	0.05
Share age: 46–55	0.25	0.07
Share age: 56–65	0.08	0.03
Share educ: Lower secondary or less; with vocational training	0.61	0.13
Share educ: Abitur with or without vocational training	0.03	0.03
Share educ: University or more	0.06	0.08
Share educ: missing	0.07	0.08
Share females	0.33	0.20
Share foreigners	0.09	0.06
ln total employment	6.37	1.63
Lagged Δ ln total employment 1978–1988	0.09	0.34
Routine share	0.14	0.55
Observations	219	

Notes: Summary statistics for the variables used in the regression analysis.

B.3 Offshorability and employment growth, evaluated at sample means

Figure 9: Offshorability and employment growth at the 3-digit industry level: different horizons



Notes: The figure depicts the relationship between the start-of-period offshorability measure and the change in log total employment between 1988 and different end years according to the regression specification (3). The graph shows the predicted growth rates for different values of ex-ante offshorability, holding the control variables at their sample means.

B.4 Robustness checks

Here, we discuss in greater detail the robustness checks described in Section 3.5 and present the detailed regression results. All the robustness checks refer to our main specification (3) and the longest possible horizon of 26 years (1988–2014) for the dependent variable.

B.4.1 Different functional forms

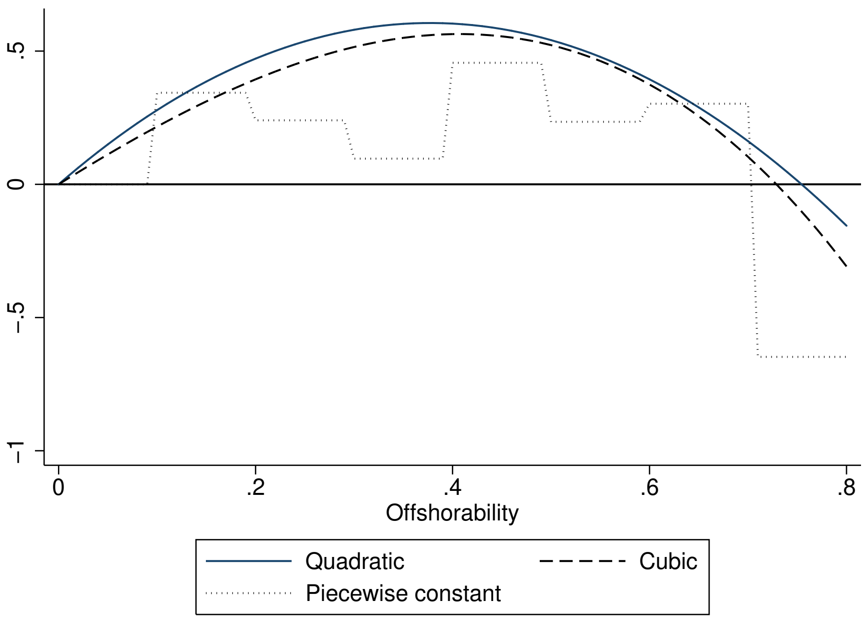
As a first robustness check, we consider different and more flexible functional forms of the offshorability term. So far, we have relied on the parsimonious, but somewhat restrictive quadratic offshorability term. We now also consider a cubic and a semi-parametric (piecewise-constant) function, respectively. For the latter, we insert separate dummy variables for the following offshorability values: [0.1; 0.2), [0.2; 0.3) [0.3; 0.4) [0.4; 0.5) [0.5; 0.6) [0.6; 0.7), [0.7; ∞); the base category is [0; 0.1).[49] Note that, while having the advantage of being the most flexible, the drawback of this approach is that some of these coefficients are identified from a fairly low number of observations.

Since the estimated coefficients are difficult to interpret and compare across specifications, we

[49]Recall that our offshorability measure varies between 0 and 0.8 across 3-digit industries in our sample.

again illustrate the relationship between the predicted employment growth (according to the estimated offshorability-related coefficients only) and offshorability graphically (cf. Figure 10).

Figure 10: Robustness: Different functional forms



Notes: The figure depicts the relationship between the start-of-period offshorability measure and the change in log total employment between 1988 and 2014 according to various specifications. "Quadratic" represents the baseline specification (3) with the quadratic offshorability term, "Cubic" the one with the cubic offshorability term, and "Piecewise constant" the one with 8 interval dummy variables capturing offshorability.

While the predictions of the quadratic and the cubic specification almost perfectly overlay each other, the non-parametric specification, admittedly, looks somewhat off and definitely less smooth. However, it shares the key characteristics with the other specifications. That is, the lowest predicted employment growth rates are reached at the bottom and the top of the offshorability spectrum, while the highest predicted employment growth rate is reached right at the center of the offshorability distribution. Taken together, this evidence lends further support to the notion of a hump-shaped relationship between employment growth and offshorability.

B.4.2 Alternative offshorability measures

We have chosen the Blinder and Krueger (2013) offshorability measure on the grounds that it was specifically designed to capture the susceptibility of a job to being relocated abroad and we have also seen that it indeed correlates quite well with actual changes in offshoring. Recall that we coded it in such a way that the top 25% (1988 employment-weighted) of occupations in terms of their offshorability score are classified as offshorable. While both convenient and in line with the existing

Table 10: Robustness: Alternative offshorability measures

	(1) BK top 25%	(2) BK top 33%	(3) BK top 20%	(4) BK std	(5) AA top 33%	(6) AA top 25%	(7) AA std
	Dependent variable: $\Delta \ln$ total employment 1988–2014						
Offsh.	3.210***	2.248*	2.833***	0.109	2.035*	0.676	0.535**
	(1.132)	(1.308)	(1.058)	(0.209)	(1.099)	(1.183)	(0.219)
Offsh. sq.	−4.255***	−3.185**	−4.239***	−0.286	−2.205**	−1.586	−0.646***
	(1.292)	(1.485)	(1.291)	(0.228)	(1.071)	(1.452)	(0.228)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	219	219	219	219	219	219	219
R sq.	0.50	0.50	0.50	0.48	0.49	0.49	0.52

Notes: * p<0.10, ** p<0.05, *** p<0.01
Standard errors (given in parentheses) are clustered at the 2-digit industry level. Each column makes use of an alternative offshorability measure. BK top 25% (the baseline): the (1988 employment-weighted) top 25% of the occupations in terms of their Blinder-Krueger offshorability score are classified as offshorable; BK top 33%: like BK top 25%, but with the top 33% of the occupations classified as offshorable; BK top 20%: like BK top 25%, but with the top 20% of the occupations classified as offshorable; BK std: standardized Blinder-Krueger offshorability score with mean 0 and standard deviation of 1 across individuals in 1988; AA top 33%: the (1988 employment-weighted) top 33% of the occupations in terms of their Acemoglu-Autor offshorability score are classified as offshorable; AA top 25%: like AA top 33%, but with the top 25% of the occupations classified as offshorable; AA std: standardized Acemoglu-Autor offshorability score with mean 0 and standard deviation of 1 across individuals in 1988. Further controls included as described in Table 2.

literature, this way of coding is of course also arbitrary.

In this subsection, we analyze to what extent our results hinge on the exact offshorability measure chosen. On the one hand, we check different alternative implementations of the Blinder and Krueger (2013) offshorability measure, i.e. we make the cut at the top 33% and the top 20% of occupations, respectively, and we consider a continuous, standardized measure with mean 0 and a standard deviation of 1.[50] On the other hand, we also consider the offshorability measure proposed by Acemoglu and Autor (2011), which is based on various items of the O*NET database.[51] For the Acemoglu and Autor (2011) measure, we consider three operationalizations: (i) the top 33% (1988 employment-weighted) of occupations are classified as offshorable; (ii) the top 25% (1988 employment-weighted) of occupations are classified as offshorable; (iii) a continuous, standardized measure with mean 0 and a standard deviation of 1 (across individuals in 1988).

Results are given in Table 10, where our baseline results based on the Blinder and Krueger (2013) top quartile measure are redisplayed in the second column for convenience. All specifications give

[50]The standardization has been carried out at the individual level.

[51]The measure can be constructed for US SOC occupations. Similar to the Blinder and Krueger (2013) measure, we have mapped it into the German 3-digit KldB1988 classification applying a series of cross-walks.

rise to a hump shape according to the point estimates, even though two of the specifications – the ones based on the standardized Blinder and Krueger (2013) and the one based on the Acemoglu and Autor (2011) top quartile measure, respectively, do not yield statistically significant estimates.[52] Still, the picture that consistently emerges from these exercises is that industries at the center of the offshorability distribution experience faster employment growth than industries at the bottom and the top of the offshorability distribution.

B.4.3 Additional control variables

Now, we address the potential concern that the relationship between employment growth and offshorability might in fact pick up other underlying factors, and hence, suffer from omitted variable bias. We address two specific concerns.

First, the relationship might be driven by long-term (and pre-existing) trends which potentially could drive both offshorability in 1988 and subsequent employment growth. To tackle this concern, we include lagged employment growth as an additional regressor. Our data allow us to go back 10 years such that we control for log employment growth between 1978 and 1988. We estimate one specification with a linear and another one with a quadratic lagged employment growth term.

Second, one might be worried that our offshorability term might capture technological change rather than offshoring. Despite the advantages of the Blinder and Krueger (2013) offshorability measure discussed above, there is of course no guarantee that it does not (also) pick up technological change. To address this concern, we augment the specification with a routineness indicator which aims to capture the susceptibility to automation and computerization, the two key elements of technological change over the period of analysis. It is based on the measures proposed by Spitz-Oener (2006) and calculated as the average share of routine tasks in total tasks across two-digit KldB1988 occupations.[53] We again estimate one specification with a simple linear and another one with a quadratic routineness indicator.

Results are given in Table 11. The most important insight is that the hump-shaped relationship between employment growth and offshorability remains robust. While coefficient magnitudes vary slightly, and in both directions – they are slightly dampened when controlling for lagged employment growth but become somewhat larger when accounting for routine task intensity – they remain highly significant and have the same sign as in the baseline specification.

As far as the additional control variables are concerned, employment growth between 1988 and 2014 is positively related to employment growth in the decade before and negatively to the ex-ante routine task intensity. The former indeed indicates that industry growth is also driven by long-term trends and the latter that forces related to automation and computerization are indeed labor-saving. Both of these factors, however, are (sufficiently) distinct from our offshorability measures.

[52] The sometimes lacking precision of the estimates is not all that surprising given that we have a fairly low number of observations and furthermore use clustered standard errors.

[53] The Spitz-Oener (2006) measures are based on the German IAB/BIBB survey, which consists of various waves. We take a simple average of the measures resulting from the 1986 and the 1992 waves, as our reference year is 1988. Furthermore, we have standardized this measure to have a mean of 0 and a standard deviation of 1 across individuals in 1988.

Interestingly, and in contrast to what we establish for offshorability, we cannot reject the null hypothesis of a monotone relationship between routineness and subsequent employment growth, as the small and insignificant coefficient of the squared routineness term indicates.

Table 11: Robustness: Additional control variables

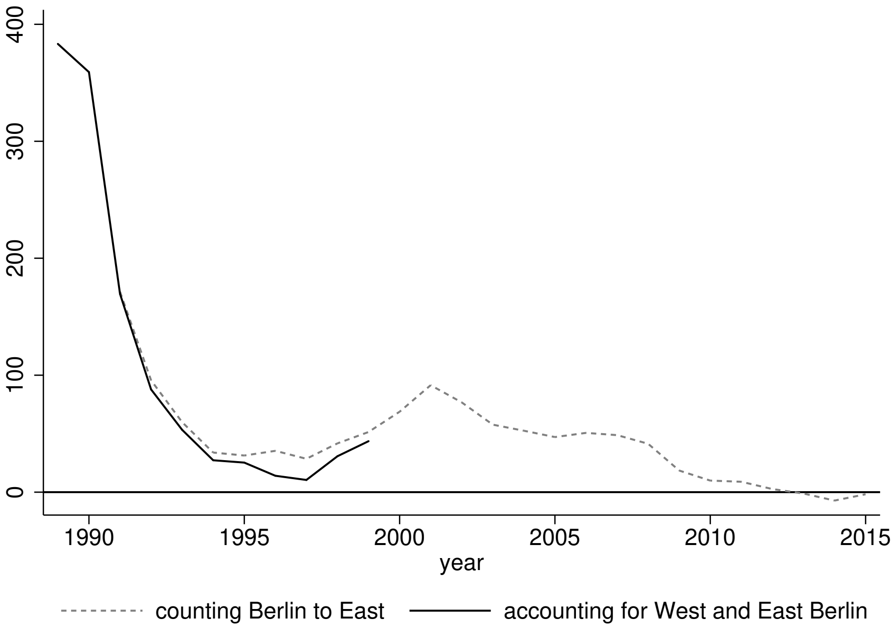
	(1) Base	(2) Lagged	(3) Lagged squared	(4) Routine	(5) Routine squared
	Dependent variable: Δ ln total employment 1988–2014				
Offshorability	3.210***	2.610**	2.526**	3.633***	3.698***
	(1.132)	(1.012)	(1.073)	(1.138)	(1.161)
Offshorability squared	−4.255***	−3.114***	−2.966**	−4.450***	−4.526***
	(1.292)	(1.128)	(1.222)	(1.272)	(1.299)
Lagged Δ ln empl.		1.354***	1.428***		
		(0.221)	(0.198)		
Lagged Δ ln empl. sq.			−0.175		
			(0.259)		
Routine share				−0.667***	−0.655***
				(0.164)	(0.181)
Routine share squared					0.0333
					(0.154)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	219	218	218	219	219
R squared	0.50	0.59	0.59	0.55	0.56

Notes: * p<0.10, ** p<0.05, *** p<0.01
Standard errors (given in parentheses) are clustered at the 2-digit industry level. Each column gives the results of a different specification. Base: redisplays the baseline results shown in Table 2, specification (3). Lagged: includes lagged log employment growth between 1978 and 1988 (linear) as additional regressor; Lagged squared: includes lagged log employment growth between 1978 and 1988 (linear and squared) as additional regressors; Routine: includes the 1988 routine share (linear) as additional regressor; Routine squared: includes the 1988 routine share (linear and squared) as additional regressors. The routine share has been calculated based on the measures proposed by Spitz-Oener (2006) and has been standardized to have a mean of 0 and a standard deviation of 1 across individuals in 1988. Further controls included as described in Table 2.

B.4.4 German reunification as a confounder?

One additional potential concern for our analysis is that, with the fall of the Iron Curtain, West German firms not only obtained new opportunities to offshore production to nearby and lower-cost destinations, but also got access to the workforce from East Germany. To the extent that West German firms shifted parts of the production process to East Germany, this is not problematic for our empirical analysis as it also implies the same type of production fragmentation that we are interested in. However, at the same time, there were large migration flows from East Germans to West Germany (e.g. Burda, 1993; Burda and Hunt, 2001). If these internal migrants got employed in West German industries according to the same uneven distribution depending on the industry's offshorability, they might confound our offshoring-related effect. To analyze the plausibility of this threat to identification, we look at the aggregate net migration flows from East to West Germany in the wake of German reunification (cf. Figure 11).

Figure 11: Net migration flows from East to West Germany (in 1000s)



Source: German Statistical Office, Fachserie 1 Reihe 1.2, various editions. Own illustration.

We depict two slightly different graphs. The first shows net migration flows from East to West between 1989 and 1999, counting East Berlin to the East and West Berlin to the West. The second shows net migration flows between 1991 and 2015, counting the whole of Berlin to the East. The second is closer to our empirical analysis, as we focus on the West German federal states only, but unfortunately not available for the important years immediately after the fall of the Berlin Wall.[54] However, in the overlapping years, both graphs move closely together. What the graph shows is that by far the largest influx of East Germans to West Germany occurred in the years 1989 and 1990. In contrast, offshoring just started to pick up in the second half of the 1990s (cf. Figure 3) and continued to grow fast in the 2000s. Thus, pure timing suggests that East-West migration, despite its non-deniable importance overall, should not affect our results. Recall that the characteristic hump shape does not show up at all by 1993, when the initial migration shock already happened

[54] We cannot distinguish East and West Berlin in the social security data.

– and should have been absorbed by the West German labor market –, but becomes pronounced much later, when these migration flows were already fading.[55]

[55]The particular timing of the East-West migration flows, together with the limitations of the social security data, also make it very difficult to conduct a formal, convincing test of the confounding hypothesis. Since the SIAB data do not contain information on the place of birth or anything the like, we can only identify internal migrants if they first show up in the East (as being employed in a job liable to social security or as receiving unemployment benefits) and later in the West. However, East Germans are only reliably included in the data from 1992 onwards. Thus, we would miss all of the initial migrants and, in addition, all those who directly moved to the West for their first post-reunification job. We therefore abstain from this possibility.