Offshoring, Firm Performance and Employment – Evidence from German Establishment Data

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Abstract:

This paper seeks to identify a causal effect of offshoring on export performance, turnover and net employment for a representative sample of German establishments from 1998 to 2004, using a difference-in-differences matching approach. Establishments that qualitatively increase their intermediate goods share from abroad exhibit a better export performance and higher turnover than matched establishments that abstain from doing so. Beyond these positive firm performance indicators, we find a positive average treatment effect on net employment change in the range of two to four percent due to the offshoring activity. These results indicate that German firms profit from increased international division of labor and gain international competitiveness without undergoing negative short-term effects on the labor market.

Key words: offshoring, export performance, employment, difference-in-differences, matching estimator.
JEL classification: F16, F23.

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1) Introduction

There is a widely held view that the dramatic increase in the world-wide production sharing has been destroying jobs on a large scale in all industrial countries. The daily press may help induce this impression since plant closures regularly receive a wide coverage, while media reports on multinational firms that increase employment at home, e.g. due to gains of market share abroad, are rare.

In contrast to that the academic literature has found ambiguous results on the employment effects of offshoring. On the one hand, there is empirical evidence based on aggregate data by Feenstra and Hanson (1996, 1999), Geishecker (2002), Hijzen, Görg, and Hine (2005), Hsieh and Woo (2005), Egger and Egger (2003, 2005), Hijzen (2007) inter alia showing a skill upgrading in industrial countries through offshoring. Low-skilled intensive production stages move to countries where low-skilled labor is relatively cheap (e.g. Helpman, 1984, Venables, 1999) and hence relative demand for low-skilled labor decreases and for high-skilled labor increases.

There is also a strong methodological case to re-examine this issue with micro data, since macro data suffer from aggregation bias, lack of appropriate control variables for skills and education, and self-selection effects (Geishecker, 2008). Micro-level evidence of labor market effects on offshoring are provided inter alia by Egger, Pfaffermayer and Weber (2003), Geishecker and Görg (2004), Marin (2005), Munch and Skaksen (2005), Broccolini et al. (2006) and Geishecker (2006, 2008). These studies typically find some evidence that offshoring leads to changes the relative demand of labor, or a decreasing demand for labor across all skill types, or an increase in income inequality.

On the other side, Becker and Muendler (2008) find that expansion of employment abroad of a German multinational firm increases job security at home. This contrasting result may, however, be driven by the proxy variable chosen for offshoring. Offshoring is measured as expansion of employment abroad of a multinational firm. However, expansion of employment abroad may not only be driven by a relocation of plants from home- to host country that *reduces* employment at home but also by an increase of the international competitiveness of the firm that *increases* employment both at home and abroad. Likewise, the measures of offshoring used in other micro studies on Germany such as Geishecker and Görg (2004) and Geishecker (2006, 2008) rely on industry-level proxies of intermediate goods trade from input-output tables.

We contribute to this literature by offering a new, refined variable for offshoring at the establishment-level. Our information relies on a survey of the IAB establishment panel covering all sectors of the German economy. Establishments were asked how important foreign intermediate inputs were relative to all intermediate inputs in production in the years 1999, 2001, and 2003. We define a qualitative change in the sourcing of foreign inputs during the two periods 1999 and 2001 and 2001 and 2003 as our treatment. Then we apply a difference-in-differences propensity score matching methods to match establishments with treatment with a control group exhibiting a very similar probability of undertaking offshoring. Finally, we estimate the average treatment effect of offshoring on turnover, exports and net employment by comparing pre-treatment values with various post-treatment values. To ensure that the conditional independence assumption is met we provide a number of balancing tests.

Our main result is that we not find a positive effect of offshoring on net employment. We explain this finding by pointing out that those firms which outsource are able to increase their international competitiveness, prompting a rise in turnover and exports. The loss in

employment through the shift in production abroad is thus dominated by an increase in the overall level of activity of the establishment and its subsequent increase in labor demand. We conclude from that those firms that make use of an increased international labor division unambiguously profit from this strategy.

The rest of this paper is organized as follows: Section 2 discusses briefly the methodology. Section 3 provides the estimation of the propensity score of offshoring. Section 4 reports balancing tests. Section 5 contains the estimates of the average treatment effect of offshoring on the three variables of interest: net employment, exports, and turnover of an establishment.

2) Methodology

The research question that lies at the heart of this paper is the following: Does increased international labor division has a positive or negative effect on German firms and the German labor market? The answer to this question has important implications from a policy perspective.

The economic literature suggests that labor market outcomes depend on the type of offshoring. While horizontal foreign direct investment (FDI) is expected to have a neutral effect on net employment, vertical FDI may have a negative impact on the domestic job market. Against this background, we will analyze three different outcome variables. Two variables will measure the plant performance in the home and foreign market. A third outcome variable seeks to determine the net employment effect:

- *Sales:* Logarithm of turnover at plant-level.
- *Exports:* Ratio of total exports over total turnover at plant-level.
- *Employment:* Logarithm of total employment at plant-level.

We follow Becker and Muendler (2008) in employing matching estimators to separate self-selection effects from causal effects of offshoring. The basic idea of a matching estimator is to estimate the probability that an establishment increases offshoring. Then one compares the

average change in the outcome variable before and after treatment of the establishments that experience treatment with those that do not receive treatment but have the same probability of doing so. For this purpose, we first estimate the probability that a plant decides to increase its offshoring activity by employing the following Logit specification (1): [1]

$$Offshoring_{i,t} = \alpha + \beta_1 Employment_{i,t-1} + \beta_2 Wage\_empl_{i,t-1} + \beta_3 Techno \log y_{i,t-1} + \\ + \beta_4 High\_skilled_{t-1} + \beta_5 Foreign + \beta_6 Time + D_B + D_R + \upsilon_{i,t}, \quad (1)$$

where the dependent variable *Offshoring* is a binary variable that takes the value of one, if the firm increases its international input factors during the period 1999-2000 or 2001-2002, and zero otherwise.

It is important to note that explanatory variables may not be affected by the treatment or its anticipation. For this reason, only time invariant or lagged variables are considered. Our Logit estimation includes the following explanatory variables with a one year time lag:

- $Employment_{i,t-1}$: Logarithm of total employment at plant i in time t-1.
- $Wage\_empl_{i,t-1}$: Logarithm of total wage per employee at plant i in time t-1.
- $Technology_{i,t-1}$: Dummy variable taking the value of one if the plant i uses state-of-the-art-technology or above-average technology in comparison to peer-group in time t-1.
- $High\_skilled_{i,t-1}$: Share of high-skilled employees as percentage of total employees at plant i in time t-1.
- *Foreign:* Dummy variable taking the value of one if a foreign owner holds majority of plant i.
- *Time:* Dummy variable taking the value of one if plant is located in West Germany and zero otherwise.

Finally, we control for industry-specific (D_B) and regional-specific effects (D_R). The error term υ is assumed to be independent of the explanatory variables and follows a standard normal distribution.

Two issues with respect to the estimation strategy are worth mentioning. First, there are a number of different matching algorithms available. Second, it remains to be discussed how to

[1] Probit and logit estimates are common in the literature for binary treatments and usually yield very similar

test for statistical significance of treatment effects, i.e. differences in outcome variables between the treatment-group and control-group.

All Propensity Score Matching (PSM) estimators compare the outcome of a treated establishment with the outcome of a comparable group of establishments that have not received treatment (control-group). Various PSM-estimators basically differ in their way of measuring the neighborhood of a treated establishment, the number of neighbors and the number of establishments that form a control group, respectively. Finally, members of the control group might be weighted in accordance to their proximity to the treated establishment.[2]

We employ a kernel matching algorithm that allows incorporating – depending on the bandwidth – a relatively large number of control group members. Thereby, more distant members – with respect to the propensity score – of the control group receive a smaller weight. The choice of the bandwidth typically involves a trade-off. On the one hand, a relatively high bandwidth implies that some of the establishments that take part of the control group might be quite different from the treated establishment, leading to a biased estimator. On the other hand, variance is expected to increase with a low bandwidth. Thus, once more it is crucial to vary the central parameter bandwidth to insure the robustness of the empirical results. We will present the results for bandwidth of 0.01, but our results are also robust to other specifications of the bandwidth. Furthermore, we present the results for nearest-neighbor-matching with 2 neighbors.

Finally, it remains to be discussed, how to gauge the statistical significance of the treatment effect. A straightforward method – often used in the literature – to estimate the standard errors is bootstrapping (see e.g., Lechner, 2002, or Black and Smith, 2004). Our standard errors will be based on bootstrapping with 200 replications. All our estimations rely on the STATA-Modul PSMATCH2 that has been developed by Leuven und Sianesi (2003).

Finally, it is important to mention that all matching estimators rely on the assumption of conditional independence. This assumption can be indirectly tested with balancing tests.

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results.

3) Data set

Our main data source constitutes the IAB Establishment Panel from the Institute for Employment Research (IAB).[3] This panel started in 1993 with 4,265 establishments in West Germany (see for instance Kölling, 2000; Bellmann, 1997) and included roughly 16,000 establishments nationwide in 2005 due to several waves of additional establishments. The IAB panel is drawn from a stratified sample of the establishments included in the employment statistics register, with the selection probabilities depending on the variation of the number of employees in the respective stratum. The stratum is defined over 16 industries, 10 categories of establishment size, and 16 German states (Länder). Large establishments are oversampled, but the sampling within each cell is random. Survey data is collected by professional interviewers of Infratest Sozialforschung on account of the German Institute of Employment Research. Participation of firms is voluntary but the response rate of more than 80% for repeatedly interviewed establishments is high. We consider all available survey years in our empirical study, covering the sample period 1993 to 2005.

Our variable of central interest in order to measure our treatment offshoring is based on the following question of the IAB establishment survey (here for the year 2003)

„From where have you received intermediate inputs and external costs in 2002, i.e. all raw materials and supplies purchased from other businesses or institutions? Please indicate for every single region whether you have received the intermediate inputs predominantly, partly or not at all from the respective region."[4]

- Old West German states

[2] For a survey on alternative matching algorithms, see for instance Caliendo and Kopeinig (2008).

[3] The IAB-Establishment Panel data is confidential but not exclusive. They are available for non-commercial research by visiting the Research Data Centre (FDZ) of the Federal Employment Agency at the Institute of Employment Research in Nürnberg, Germany. For further information, we refer to http://fdz.iab.de/en.

[4] Translated by authors. The original question is as follows: *„Woher haben Sie im Jahr 2002 das eingesetzte Material – also Roh- und Betriebsstoffe, Vorprodukte oder Handelsware – bezogen? Sagen Sie mir bitte zu jeder einzelnen Region auf dieser Liste, ob Sie Ihr Material von dort überwiegend, teilweise oder gar nicht bezogen haben."*

- New German states (East Germany) incl. Berlin.
- European Monetary Union states (excl. Germany): Austria, Belgium, Finland, France, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.
- Other foreign states.

The same question was also surveyed in the years 1999 and 2001. Consequently, the data allows us to measure the impact of an increase in the share of international input factors on plant specific performance for two periods in time (1999-2000 and 2001-2002, respectively).

We define our treatment variable "offshoring" as follows: An increase in intermediate goods from other foreign states measured as an upgrade from „not at all" to „partly" or from „partly" to „predominantly" in the year 1999 or 2000. The variables included in the propensity score model have to fulfill two requirements: i) influence both the participation decision and the outcome variable and ii) be unaffected by the participation itself. Hence, we include time varying variables only lagged by one period. The underlying assumption is that the management decision to outsource or not to outsource is taken one year before its realization. Furthermore, we compare pre-treatment values of outcome variable in the period 1998 with varying post-treatment values (t=0, t=1 and t=2). Thereby, t=0 is equivalent to the first year, in which the offshoring activity has been completed, namely the year 2000. Since changes triggered by the offshoring event might not materialize immediately, we measure changes up to four years in total or up to two years after the completion of the offshoring.

For the second time period the treatment offshoring is defined analogously for an increase in intermediate goods in the year 2001 or 2002. The selection variables date back to 2000 and changes in the outcome variables are measured as the difference between 2000 and 2002, 2003 or 2004, respectively. We pool the two time periods for which we are able to define offshoring in order to profit from efficiency gains.[5]

4) Estimating the Probability of Offshoring

Column (1) of Table 1 reports our preferred Logit specification. We find that the decision for offshoring is positively and highly significantly correlated with the size of the plant and its

[5] Pooling tests confirm that this empirical strategy is valid.

average wage costs. Furthermore, foreign-owned plants that exhibit relatively high level of technology and employ more high-skilled workers are more inclined to offshoring.

Table 1: Logit Estimates of Propensity Score

	Preferred model	Modified model	Offshoring *cum* restructuring
Log total employment (t-1)	0.1303***	0.3966***	0.4572***
	(5.72)	(4.92)	(7.19)
Log total employment^2 (t-1)		-0.0327***	
		(3.44)	
Log wage per employee (t-1)	0.2275***	0.1636**	0.6957***
	(3.11)	(2.15)	(2.59)
Technology (t-1)	0.2194***	0.2208***	-0.5223***
	(3.08)	(3.10)	(2.60)
High-skilled (t-1)	0.3564***	0.4563***	1.0755**
	(2.75)	(3.42)	(2.54)
Foreign ownership	0.4166***	0.4360***	0.1826
	(3.49)	(3.65)	(0.62)
Time dummy	-0.0486	-0.0497	-0.2289
	(0.57)	(0.58)	(0.80)
Pseudo R-squared	0.06	0.06	0.16
Observations	8466	8466	7315

Notes: z-values in parenthesis; definition of variables included in the matching: *Total employment:* log of number of employees per plant, *Wage per employee:* log of average wage per employee, *Technology:* Dummy=1 if plant has above average or state-of-the art technology, *High-skilled:* share of high-skilled workers of total employment, *Foreign ownership:* Dummy=1 if plant is majorly held by a foreign owner.industry and regional dummies are employed but not reported; *** denotes 99% significance level, ** 95% significance level, * 90% significance level; treatment is defined as an increase in vertical integration between either in the year 1999-2000 of 2001-2002 for a certain plant; non-treatment is defined as those plants that do not increase their vertical integration during the same time period.

In column (2) we follow Dehejia (2005) and add a quadratic size term to our baseline specification as a robustness check. Finally, in column (3) we propose a different treatment variable. While our control group remains the same, we now regard a plant as treated if it incurs offshoring as defined above and at the same time goes through a plant restructuring. Restructuring is measured as a discrete organizational change, where parts of the plant are shut-down, sold-off or spun-off. Interestingly, offshoring cum restructuring is more likely to occur, if the plant is not at the technology frontier of its branch. Furthermore, foreign ownership does not have any significant explanatory power any longer.

5) Balancing Tests

Matching estimators are biased unless the conditional independence assumption holds, i.e. the outcome in the treatment and the no-treatment case are independent of unobservable

characteristics of the participation decision. Under this assumption the selection variables are balanced between the treatment and matched-control group (Rosenbaum and Rubin, 1983). A lack of balancing points at a violation of the conditional independence assumption or other misspecifications of the propensity score estimates. We employ two different balancing tests. The first one is the standardized difference between treatment and matched-control group of all selection variables at a time (see, e.g., Caliendo and Kopeinig, 2008). Although there is no significance level on this statistic available, Rosenbaum and Rubin (1985) call the standardized difference large if it exceeds 20 percent. The second test is a mean-difference t-test with standard deviations differing in treatment and matched-control group.

Table 2 shows the balancing tests. We do not find any indication for a violation of the conditional independence assumption with respect to the first balancing test. The standardized difference between treatment and matched-control group of all selection variables is displayed in column 4 (percent bias). Each selection variable exhibits a percent bias well below 20 percent, with the highest standardized bias being 4 percent. The second balancing test yields similar results. There is not a single case, where the mean-difference test between the treatment-group and the control-group is significant at the conventional levels.

Table 2: Balancing Tests from Kernel Matching

Covariate	Mean treatment group	Mean control group	Percent bias	Percent bias reduction	Mean-diff. t-stat (p-value)	Regression-based tests F-stat (p-value)
Total employment	3.7338	3.7338	1.2	96.5	0.26 (0.79)	0.83 (0.51)
Wage per employee	7.3771	7.3771	-0.2	99.5	-0.04 (0.97)	1.24 (0.29)
Technology	0.7389	0.7338	1.1	91.2	0.27 (0.79)	0.63 (0.63)
High-skilled	0.3801	0.3818	-0.6	59.4	-0.14 (0.89)	1.54 (0.19)
Foreign ownership	0.0968	0.0867	4.0	82.0	0.81 (0.41)	2.15 (0.07)

Notes: Definition of variables included in the matching: *Total employment:* log of number of employees per plant, *Wage per employee:* log of average wage per employee, *Technology:* Dummy=1 if plant has above average or state-of-the art technology, *High-skilled:* share of high-skilled workers of total employment, *Foreign ownership:* Dummy=1 if plant is majorly held by a foreign owner. Balancing of industry, regional and time dummies is not reported; all dummies have a percent bias below 3; mean-diff. is mean difference test with standard deviations differing between treatment and control group.

Third, we perform the Hotelling test on quintiles that tests balancing within each quintile over all variables jointly. Table 3 displays the results for the Hotelling test, showing once more no significance imbalance.

Table 3: Hotelling's T-squared Tests by Propensity Score Quintile

Quintile	T-squared statistics	F-test statistics	p-value
First	41.000	1.254	0.157
Second	20.536	0.609	0.961
Third	40.495	1.200	0.202
Fourth	31.485	0.905	0.626
Fifth	35.927	1.065	0.369

Finally, Dehejia (2005) suggests checking the sensitivity of the matching estimates to minor changes in the propensity score model. We added the squared total employment number to our baseline specification without any qualitative change in either the balancing tests or the matching results.[6] Hence, the propensity score specification appears to be robust and reliable. To sum up, none of the balancing tests indicate that there is a violation of the conditional independence assumption. This implies that differences in the outcome variables between the two groups will stem from differing offshoring strategies.

5) Average Treatment Effects of Offshoring on Net Employment, Exports, and Turnover

Table 4 gives the results for the outcome variable job net flows. Standard errors from bootstrapping with 200 repetitions are displayed in parentheses. Interestingly, we find a positive and robust treatment effect on net employment at the plant-level. All point estimates have a positive coefficient and also vary relatively little with respect to the modified model.

Table 4: Impact of Offshoring on Log Employment (Kernel Matching)

Time	OLS	ATT Preferred Model	ATT Modified Model
	(1)	(2)	(3)
1	0.0201*	0.0214**	0.0200*
	(0.0110)	(0.0106)	(0.0105)
2	0.0223**	0.0418***	0.0401***
	(0.0909)	(0.0136)	(0.0135)
3	0.0504***	0.0439***	0.0453***
	(0.0161)	(0.0152)	(0.0151)

Notes: Standard errors in parentheses. For the matched sample standard errors are generated via boostrapping (200 replications); *** denotes 99% significance level, ** 95% significance level, * 90% significance level.

The average treatment effect is in the range of 2.1 to 4.4 percent. These results indicate that an increase in offshoring has a discernible positive impact on the net employment situation for German establishments.

[6] Results are available from the authors upon request.

The empirical results for the outcome variable sales are presented in Table 5. We find a very robust positive average treatment effect in the range of 5 to 7.4 percent at the 99 confidence level. Thus, establishments that increase their foreign intermediate inputs exhibit higher turnover than comparable establishments that abstain from deepening their international labor division. Assuming that growth in turnover is positively correlated with growth in profits, we can expect that treated establishments gain competitiveness at home and abroad alike.

Table 5: Impact of Offshoring on Log Sales (Kernel Matching)

Time	OLS	ATT Preferred Model	ATT Modified Model
	(1)	(2)	(3)
1	0.0447***	0.0502***	0.0495***
	(0.0142)	(0.0150)	(0.0153)
2	0.0488***	0.0583***	0.0611***
	(0.0164)	(0.0190)	(0.0186)
3	0.0549***	0.0743***	0.0769***
	(0.0195)	(0.0209)	(0.0208)

Notes: Standard errors in parentheses. For the matched sample standard errors are generated via boostrapping (200 replications); *** denotes 99% significance level, ** 95% significance level, * 90% significance level.

Companies with strong cash-flows have a greater flexibility in financing new investments. Consequently, they are more capable of staying near the technological-frontier in the respective industry. Furthermore, stronger turnovers stemming from increased offshoring will likely be associated with stronger international competitiveness, which allows such companies to sustain or even increase their international market share.

Table 6: Impact of Offshoring on Exports (Kernel Matching)

Time	OLS	ATT Preferred Model	ATT Modified Model
	(1)	(2)	(3)
1	1.2987***	0.9359**	0.9175**
	(0.3840)	(0.3681)	(0.3755)
2	1.7460***	1.1623***	1.2177***
	(0.4663)	(0.4280)	(0.4413)
3	2.6357***	1.3176**	1.4682***
	(0.5680)	(0.5551)	(0.5583)

Notes: Standard errors in parentheses. For the matched sample standard errors are generated via boostrapping (200 replications); *** denotes 99% significance level, ** 95% significance level, * 90% significance level.

At the same time, restrictions on offshoring that hinder plants to profit from their optimal input-mix between domestic and foreign input factors are expected to have a detrimental effect on competitiveness. Finally Table 6, shows that treated plants exhibit a higher share of total revenues abroad due to offshoring (at least at the 95 percent confidence level).

Finally, we would like to compare our results for the impact of offshoring on the German labor market with other recent empirical studies. Based on a propensity-score matching, Becker and Mündler (2008) find that expanding international firms retain more jobs in Germany than competitor without foreign expansions. This effect seems especially pronounced for high-skilled workers. Becker and Mündler (2008) exploit a newly created employer-employee-data set that combines FDI information from the Bundesbank's MIDI data set and social security records provided by the German Federal Labor Agency (BA). In a similar vein, Buch and Lipponer (2007) find no evidence for higher elasticity for labor demand (in the home country) due to an increase in multinational firms' activities. Consequently, multinational activity does not increase job insecurity. In contrast to that Geishecker (2006) finds that greater openness increases job insecurity. His analysis relies on the German Socio-Economic Panel.

6) Conclusion

To be completed

6) References

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7) Appendix

Table A1: Frequency Distribution of Treated and Non-treated plants by Propensity Score Quintile

Quintile	Outsourcing plants	Non-outsourcing plants
First	76	1380
Second	124	1331
Third	201	1255
Fourth	300	1155
Fifth	383	1072

Table A2: The Impact of Offshoring on Log Employment, Log Sales and Exports (Nearest Neighbor Matching)

Time	Employment	Sales	Exports
1	0.0315**	0.0515***	1.1143**
	(0.0136)	(0.0187)	(0.4592)
2	0.0532***	0.0612***	1.3417***
	(0.0178)	(0.0226)	(0.4896)
3	0.0541***	0.0833***	1.2853*
	(0.0196)	(0.0274)	(0.6877)

Notes: Standard errors in parentheses. Nearest-neighbor matching with two neighbors and caliper=0.05. For the matched sample standard errors are generated via boostrapping (200 replications); *** denotes 99% significance level, ** 95% significance level, * 90% significance level.