Offshoring Jobs:
Are Manual Workers the Victims of Mass Lay-Offs?[1]

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Friday, 31 July 2015

Abstract

We empirically analyse which types of jobs disappear when firms offshore parts of the production process. We use representative linked employer-employee data for Germany, supplemented with occupational-level offshoreability measures from task data. Jobs are classified according to their individual offshoreability according to the Spitz-Oener (2006) classification. As identification strategy we use a dynamic difference-in-difference framework to analyse offshoring firms before and after a mass lay-off takes place in comparison to firms without mass lay-offs and/or without offshoring activity. We find that offshoring firms which experience mass lay-offs employ more non-routine interactive jobs before the mass lay-off takes place. In the mass lay-offs, they shed predominantly manual jobs and increase the share of cognitive and non-routine analytical jobs afterwards.

Keywords: offshoring, mass lay-off, difference-in-differences, trade in tasks, offshoreability

JEL Classification: J63, F16, F61

[1] This paper is part of the research project 'Trade in tasks – potentials for internationalization and their effects on the wage structure and composition of employment', funded by the German Research Foundation (DFG) (BO 2793/3-1).

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1 Introduction

The empirical trade literature has increasingly studied the determinants and impacts of offshoring at the firm level. A lot of attention has been put to firm-level determinants of offshoring, e.g. finding that mostly large and productive firms engage in offshoring and that these firms might also gain in productivity from offshoring (for a recent empirical analysis see Smolka and Kohler 2014, for a theoretical overview see Acemoglu and Autor 2011).

The literature so far lacks a more detailed, i.e. individual-level, analysis of how offshoring firms differ exactly before and after the offshoring takes place. Therefore, we combine the literature on offshoring with the recent literature on trade in tasks, i.e. the notion that certain types of jobs, i.e. occupations, are more easily tradeable across countries than others (for an overview, see Autor 2013). Following this latter literature, offshoring is no longer restricted to low-skilled jobs, but to jobs that are more routine and less interactive. The question then is how do firms that engage in offshoring differ in terms of their workforce's offshoreability before and after offshoring takes place.

To answer this question, we perform an empirical investigation that combines representative German linked employer-employee data with information on the firms' workforces' offshoreability, which is drawn from German task data. We measure offshoreability according to Spitz-Oener (2006) in five categories according to the tasks performed at the workplace: routine manual, routine cognitive, non-routine manual, non-routine interactive, and non-routine analytic jobs. We merge the task data to the LIAB at the occupational level, comparable to Boockmann (2014) or Fedorets et al. (2014). Our dependent variables are the task shares of the firms' workforce.

We know from the literature that offshoring firms differ from non-offshoring firms in both a number of observable and unobservable factors. While we can control most for the former, identification of the latter would normally be based on controlling for firm-fixed effects (Wooldridge 2002). As our empirical identification strategy, we therefore use an event-study analysis that acknowledges time-variant unobserved factors that might influence offshoring decisions by firms. For this purpose, we focus on firms which offshored parts of the production process using mass lay-offs. Methodologically, we perform a dynamic difference-in-differences approach (see Imbens and Wooldridge 2009), which allows us to identify differences in the firms' workforces' offshoreability levels before and after the offshoring (and mass lay-off) has taken place.

The rest of the paper is structured as follows. Chapter 2 will shortly summarise the two strands of literature on offshoring and offshoreability, and mass lay-offs. We describe the data we employ in Chapter 3. After that we explain our empirical strategy and present the results in Chapter 4, while Chapter 5 concludes.

2 Literature Review

2.1 Offshoring at the Firm Level

Offshoring is defined as a firm's decision to relocate the production of intermediate inputs to a foreign country. We can further differ between offshoring within the firm boundary (which could be interpreted as vertical FDI), and outside the firm boundary (which represents international outsourcing).

Firms offshore parts of the production process when they to reduce production costs, i.e. to become more productive, e.g. through wage differentials between the home country and the offshoring location, higher quality, or more variety.[3] These savings are compared to the costs of offshoring, e.g. setting up a plant, transportation and communication costs, and frictions. Usually, heterogeneous trade models predict that firms sort themselves into offshoring which are more productive even before the offshoring takes place (Antras and Yeaple (2014).[4]

Empirically, this sorting mechanism has been tested quite extensively. Görg et al. (2008) conclude in their literature survey that offshoring firms are larger, more human capital intensive, and have a higher share of exports in total sales, i.e. they are more internationally active on other fields as well. However, there is an ongoing discussion, similar to the one on exports, on whether the relationship between offshoring and productivity is a causal effect or a selection effect (see, e.g. Kohler and Smolka 2014 for the most recent empirical contribution). Evidence for Germany is mostly confined to the sector-level data on offshoring (see, for a discussion, Eppinger 2014 and for recent evidence Schwörer 2013). Wagner (2012) offers a review of recent studies on the relationship between imports (the use of foreign intermediates) and firm performance. Evidence for other countries is provided, e.g., by Bas and Strauss-Kahn (2014) for France, or Serti et al. (2010) for Italy.

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3 Offshoring might also have possible effects on production or labour costs at home, for example through a positive effect on the labour supply (Grossmann and Rossi-Hansberg 2008) or a negative effect on the employees' bargaining power (Skaksen 2004).

4 This sorting pattern depends crucially on fixed cost ranking. Especially for middle two categories, this remains unclear. For example, Kohler and Smolka (2012) find evidence from Spain on reverse patterns.

3 Data

3.1 The LIAB Dataset

To investigate the relationship between mass lay-offs and the composition of a firm in terms of offshoring potentials our primary dataset is the LIAB dataset from the Institute for Employment Research (IAB) in Nuremberg, more precisely the LIAB cross-sectional Model 2 1993-2010.[5] It is a linked employer-employee dataset with rich information based on a representative annual firm-level survey (the IAB Establishment Panel), together with personal data generated in the labour administration and social security records from almost all employees working in these firms. The individual data (the Integrated Employment Biographies, IEB) is drawn from official registers and is of very high quality, but the number of individual variables observed is limited. We use personal information on all individuals employed in a firm surveyed in the IAB EP and aged between 15 and 65, excluding home workers and working family members, as well as individuals earning less than 450 euros a month.

The IAB Establishment Panel is a representative sample of about 1 % of German firms that is stratified over industries and firm size classes. Hence, large firms are slightly overrepresented, such that the data covers about 7 % of all German employees. It bases on the population of all firms in Germany with at least one employee subject to social security. The survey is conducted in personal interviews with senior staff or personnel managers, and has high response rates and low panel attrition. The questionnaire focusses on the firms' personnel structure, development and policy, and offers extensive information on firm characteristics. We restrict our data to firms from manufacturing and service industries with at least five employees. We access the data through remote-data access and guest visits at the Research Data Centre (Forschungsdatenzentrum, FDZ) at the IAB.

To account for confounding factors both influencing the probability of mass lay-offs and offshoring potentials in the workforce, we control for a large number of further covariates. The firm-level characteristics are comparable to the ones used by Addison et al. (2011). We can control for collective bargaining status (including orientation and the existence of wage cushions), in- and outsourcing behaviour, the share of vacancies, the share of workers with temporary contracts, the churning rate, investment activity, firm age, foreign and public

5 The LIAB data from the IAB, see Heining et al. (2013).

ownership, modern technical assets, status as a single firm, status as limited firm, the existence of human resource management problems, and industry, region, firm size and year dummy variables.

Furthermore, there exist additional variables which might influence our dependent variables, but which have a significant share of item-non-response. Therefore, we include them in some specifications, but always control for sample selection bias estimating the restricted model on the restricted sample. These variables include the natural logarithm of total investments, the share of expansion investments, standard weekly working time, the share of exports, an overtime dummy, the existence of firm-sponsored training and performance-related pay, and expectations on business outlook, rising turnover and rising employment levels.

Additionally, based on individual-level data, we incorporate firm-specific means of employee characteristics with respect to sex, nationality, tenure, age, qualification (apprenticeship, having completed an apprenticeship, and university education), occupational status (blue collar worker), working time (part-time) and daily wages.

3.2 Offshoreability in the BIBB Qualification and Career Survey

For the information on job tasks we use the Qualification and Career Survey, a representative sample of the working population in Germany. The survey is carried out in repeated cross-sections since 1979 in intervals of about five years and it is based on telephone interviews with up to 30,000 economically active individuals per cross-section.[6]

The data contain a variety of information on individual employees and their jobs. The variables range from basic personal information such as age, education, job tenure and wages, to job characteristics and working conditions. Concerning wages, monthly gross income, i.e. the salary before deduction of taxes and social-security contributions has been surveyed in the questionnaire. We restrict our analysis to the three most recent waves as this matches the time span of our firm data and guarantees a good comparability of job characteristics over time.

The main advantage of the data comes from the detailed questions on tasks performed at the workplace and on various job characteristics. The data contain several variables describing in detail the assignment, the content, and the attributes of an individual's job. The data contains

[6] The BIBB/BAuA Employment Surveys, see Hall et al. (2014).

rich information with respect to job characteristics.[7] Further variables refer to individual and household information, including a fine grained Kldb2010/1992 3-digit level job classification, which is the same as in the personal records of the LIAB data.[8].

The Qualification and Career Survey contains information on most of the job characteristics which have been identified in the economic literature as relevant determinants of the offshoreability of jobs. While other studies such as the one by Brändle and Koch (2014) make use of a wide range of characteristics for job offshoreability, we restrict ourselves to the one used by Spitz-Oener (2006), which is more suitable for this analysis, as it provides a simple measure at the occupation level. Figure 3.1 presents the idea: depending on the tasks performed, a job is classified into one of five categories using a routineness and interactivity differentiation.

Figure 3.1: Assignment of Tasks to Five Classifications of Offshoreability

Classification	Tasks
Nonroutine analytic	Researching, analyzing, evaluating and planning, making plans/constructions, designing, sketching, working out rules/prescriptions, and using and interpreting rules
Nonroutine interactive	Negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, and employing or managing personnel
Routine cognitive	Calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature
Routine manual	Operating or controlling machines and equipping machines
Nonroutine manual	Repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving or accommodating

Source: Spitz-Oener (2006: 243).

For our investigation we calculate the share of each job classification on the Kldb1988 2-digit level of occupations. We then merge this very detailed information to the exact same occupation classifications in the LIAB data, as shown in Figure 3.2.

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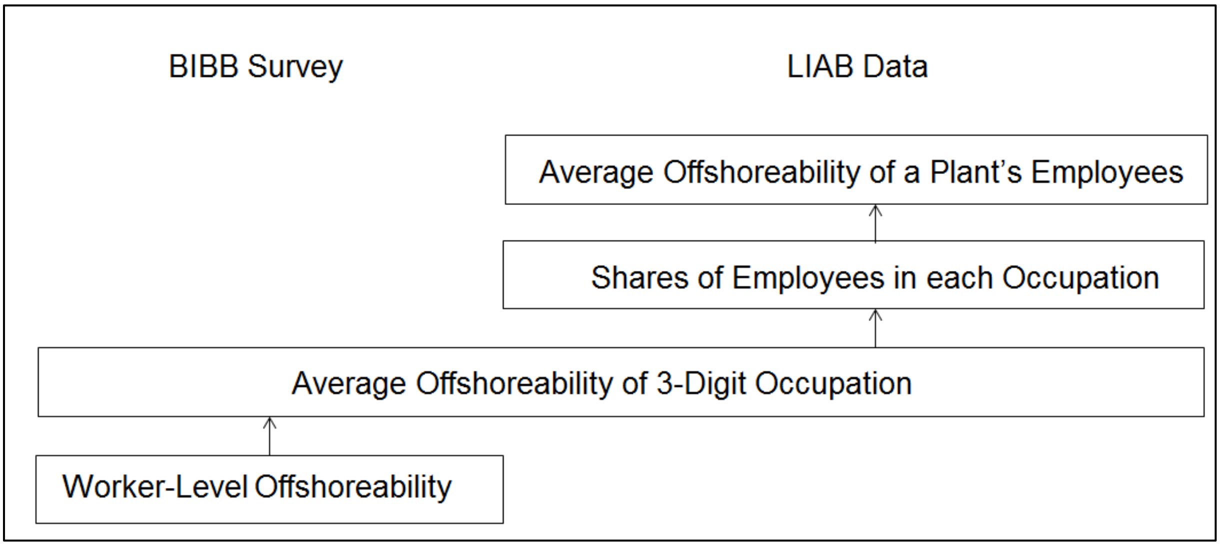
7 The information used is similar Spitz-Oener (2014). See also Rohrbach-Schmidt and Tiemann (2013) for a recent overview of the measurement of skills and tasks on the basis of the Qualification and Career Survey.

8 This classification is based on the KldB 88 (“Klassifizierung der Berufe”), which is a classification of professions quite common in German datasets and literature. Contrary to the International Standard Classification of Occupations (ISCO), it is based on the actual type of professional activity, and not on skill levels.

Figure 3.2: Linking the Offshoreability Information to the Firm Data



Source: Own representation.

As our level of analysis is the firm, we then aggregate this information similarly to the individual information from the IEB to the firm level. Our variables of interest then comprise five shares of job categories, depending on the occupations of the workforce in each firm.

Regarding the time variance of the data, we pursue two approaches. First, we calculate average job category shares for each occupation over time and merge them to the LIAB. Changes over time in these shares then only compose changes between occupations inside the firm. As an alternative, we calculate the job category shares for each cross-section of the BIBB/BAuA survey (1991, 1998, 2006, and 2012) separately, merge them to the LIAB and use a linear approximation of these four points in time to also capture changes in job shares within occupations.

3.3 Offshoring and Mass Lay-Offs

The LIAB dataset contains a set of variables, namely responses to different questions directed at firm managers or high personnel staff on outsourcing and offshoring (cf. Brändle 2015). Unfortunately, items on offshoring are not included in every wave, and different items are asked across waves. For example, the relevant item in the 2008 wave reads:

"Did your company/your department contract out work, which was previously carried out by the company itself to other companies in the last financial year, i.e. 2007? [Yes] [No] and Where is this work carried out now? [At home] [Abroad] [Both at home and abroad]"

This information particularly suits the investigation of actual offshoring as it precisely follows the definition of imports of intermediate inputs. Note that the question is asked in a way that it only identifies an increase in imported intermediates, such that level effects, that are particularly affected by self-selection, e.g. of productive firms into offshoring, do not play a role here.

We use the information on different variables to calculate a combined indicator whether the firm has engaged in offshoring activity. We use information of firms that have increased their inputs through offshoring or outsourcing, that have relocated parts of the firm, that have increased their share of inputs through imports, and that have re-organised their production process through buying additional intermediates.[9]

For calculating mass lay-offs, we calculate differences in yearly employment levels measured on June 30th of each year and apply the definition of § 17 of the German KSchG.[10] First, mass lay-offs are only defined in firms above 20 employees, such that we drop all small firms. For firms with 20 to 60 employees a mass lay-off needs to be over 5 employees lost, for firms with 60 to 500 employees a mass lay-off needs to be over 25 or at least 10 % of the employees, and for firms with more than 500 employees a mass lay-off needs to be over 30 employees.

Using this calculation, 15.44 % of all firm*year combinations count as a mass lay-off. Over time, only 62.26 % of all firms have not experienced a mass lay-off, while 18.94 % experience one mass lay-off, 8.33 % experience two mass-layoffs and so forth up to a single digit number of firms that experience a mass lay-off in all 15 years of the panel data set. For our analysis we only look at the first mass lay-off.

4 Empirical Analysis

4.1 Empirical Strategy

The shares of each job category, the stylized estimation equation for the different models reads as follows:

$$\mathrm{Y_{it}} = \beta_1 + \beta_2 \mathrm{off_{it}} + \boldsymbol{\gamma}\, \mathbf{X_{it}} + \delta\, \mathrm{year_t} + \varepsilon_{it} \tag{1}$$

Here, $\mathrm{Y_{it}}$ represents the dependent variables. We present linear probability models, while the nature of the dependent variables would suggest using fractional logit or other models that

[9] Information is available for the years 1998, 1999, 2000, 2001, 2003, 2004, 2007, 2008, 2010.

[10] The original law states that the mass lay-off happens during a 30 days interval.

account for the fact that their range is only between zero and one. The subscript i represents firms at time t. The dummy variable off_{it} indicates the existence of a relocation abroad through a mass lay-off, while the vector $\mathbf{X_{it}}$ contains confounding factors, year_{t} represents year dummies, and ε_{it} is the error term. In order to account for multiple observations of individuals or firms over time we use cluster-robust standard errors.

Estimating equation (1) would allow us to establish a correlation between offshoring and job category shares. However, such a relationship can not only come about because offshoring affect job category shares, but also because of selection of firms or other unobserved factors. To get closer to a causal interpretation, we use information with respect to changes in offshoring status in the longitudinal dimension. We estimate difference-in-differences (DiD) models. Our estimation equation reads:

$$\text{Y}_{\text{it}} = \beta_1 + \beta_2 \text{off\_ever}_{\text{i}} + \beta_3 \text{post\_off}_{\text{it}} + \boldsymbol{\gamma}\, \mathbf{X_{it}} + \delta\, \text{year}_t + \varepsilon_{\text{it}} \qquad (2)$$

Since the ‘treatment’ does not occur at the same moment in time for all firms, we follow Imbens and Wooldridge (2009) to discern two effects. The time-invariant dummy variable $\text{off\_ever}_{\text{i}}$ captures the selection effect of firms into the treatment and control group. It is set equal to one if the firm engages in offshoring at some point in time, while it is zero if the treatment does not occur at any point. This allows us to see whether offshoring is introduced in firms with different job category shares before its adoption (reversed causality) or whether firms with different job category shares sort themselves into engaging in offshoring more probably (selection effect). The variable $\text{post\_off}_{\text{it}}$ captures the exposure to the ‘treatment’, indicating whether a firm i in period t has offshored in the past (treatment or DiD effect). Using this approach we can differentiate between differences before, after and because of the treatment.

4.2 General Results

Table 4.1 displays the full regression table for mass lay-offs, Table 4.2 for mass lay-offs that coincide with offshoring activity. Each column presents the results for a different job task share, while all models use the same set of control variables across the columns.

First, we analyse the selection effect defined by the pre-mass lay-off conditions. We can see that firms that later perform mass lay-offs have a 1.1 percentage points higher share of routine manual jobs than firms that do not perform mass lay-offs. The contrary can be said for all other dependent variables. The share of routine cognitive jobs is 1.6 percentage points lower, the share of non-routine manual jobs is 1.1 percentage points lower, and especially the shares of non-routine interactive and non-routine analytic jobs are 2.7 and 3.3 percentage points lower. This indicates that mass lay-off firms are somewhat special.

Table 4.1: Job Task Shares before and after Mass Lay-Offs, OLS Estimation

Dependent Variable:	Routine Manual	Routine Cognitive	Non-Routine Manual	Non-Routine Interactive	Non-Routine Analytic
Pre-Mass Lay-Off	0.0113*	-0.0166***	-0.0118**	-0.0275***	-0.0336***
	(0.0063)	(0.0041)	(0.0058)	(0.0046)	(0.0066)
After Mass Lay-Off	-0.0058	-0.0011	-0.0325***	0.0050	0.0043
	(0.0062)	(0.0040)	(0.0060)	(0.0045)	(0.0063)
Single Plant (Reference Category)					
Headquarter	-0.0128**	0.0010	-0.0108*	0.0181***	-0.0016
	(0.0054)	(0.0037)	(0.0061)	(0.0042)	(0.0059)
Branch Plant	0.0298***	-0.0414***	0.0436***	-0.0298***	-0.0704***
	(0.0044)	(0.0031)	(0.0049)	(0.0034)	(0.0047)
Collective Bargaining Agreement	0.0328***	-0.0346***	0.0506***	-0.0219***	-0.0575***
	(0.0041)	(0.0030)	(0.0040)	(0.0033)	(0.0045)
Working Owner	-0.0134***	0.0032	0.0073	0.0143***	0.0048
	(0.0041)	(0.0027)	(0.0049)	(0.0030)	(0.0042)
Firm Age	-0.0019***	0.0001	-0.0008**	0.0004**	0.0005*
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Foreign Ownership	-0.0383***	0.0322***	-0.0435***	0.0337***	0.0649***
	(0.0086)	(0.0046)	(0.0059)	(0.0058)	(0.0082)
Business Volume: Sales (Reference Category)					
Total Assets	-0.1214***	0.0764***	-0.2647***	-0.0015	0.0412
	(0.0266)	(0.0209)	(0.0389)	(0.0237)	(0.0305)
Total Premium Paid	-0.1523***	0.0950***	-0.2837***	0.0039	0.0718**
	(0.0327)	(0.0209)	(0.0404)	(0.0239)	(0.0311)
Budget Volume	-0.0967***	0.0777***	-0.0215*	0.0686***	0.1893***
	(0.0079)	(0.0063)	(0.0131)	(0.0064)	(0.0099)
Works Council	-0.0480***	0.0634***	-0.0306***	0.0486***	0.1066***
	(0.0052)	(0.0036)	(0.0059)	(0.0040)	(0.0057)
Public Ownership	-0.0821***	0.0574***	-0.1338***	0.0265***	0.1044***
	(0.0074)	(0.0059)	(0.0122)	(0.0064)	(0.0097)
Share of Flexible Workers	-0.0148	-0.2575***	-0.0679***	-0.1874***	-0.3539***
	(0.0135)	(0.0135)	(0.0172)	(0.0142)	(0.0179)
Limited Company	0.0152***	0.0125***	-0.0158**	-0.0262***	0.0019
	0.0152***	0.0125***	-0.0158**	-0.0262***	0.0019
Exporting Plant	0.0081	0.0390***	-0.0598***	-0.0038	0.0652***
	(0.0056)	(0.0031)	(0.0044)	(0.0039)	(0.0053)

Industry Dummes (9)	Yes***	Yes***	Yes***	Yes***	Yes***
Year Dummies (15)	Yes	Yes	Yes	Yes	Yes
Firm Size Dummies (5)	Yes	Yes	Yes	Yes	Yes
Constant	1.3218***	0.8983***	1.1321***	0.8300***	1.0086***
	(0.0159)	(0.0124)	(0.0225)	(0.0133)	(0.0187)
No. of Obs.	69966	69966	69966	69966	69966
No. of Clusters	18937.00	18937.00	18937.00	18937.00	18937.00
F-Stat	655.01	164.51	672.27	342.58	201.23
R squared	0.41	0.24	0.48	0.40	0.29

Note: Cluster-Robust standard errors in parentheses: p<0.10, ** p<0.05, *** p<0.01; Dummy variables contain, firm size classes, industry classification, and year. Source: LIAB QM 9310, own calculations.

Next, we turn to the job task shares after the mass lay-off has taken place. We can see that mass lay-off firms have a 3.2 percentage points lower share of non-routine manual jobs than firms which do not perform a mass lay-off at all. The other dependent variables do not differ significantly.

However, if adding up both difference-in-differences coefficients, we can see that mass lay-offs especially shed routine and non-routine manual jobs. On the contrary, the mass lay-off plans have a higher share of routine cognitive, non-routine interactive and non-routine analytic jobs after the mass lay-off, as compared with before.

Next, we turn to firms where the mass lay-off happens simultaneously with offshoring activity. The results are depicted in Table 4.2, in a comparable way as before.

Table 4.2: Job Task Shares before and after Offshoring, OLS Estimation

Dependent Variable:	Routine Manual	Routine Cognitive	Non-Routine Manual	Non-Routine Interactive	Non-Routine Analytic
Pre-Offshoring	-0.0437***	0.0126**	-0.0373***	0.0280***	0.0236***
	(0.0082)	(0.0055)	(0.0066)	(0.0061)	(0.0087)
After Offshoring	-0.0057	0.0056	0.0082	0.0109*	0.0177*
	(0.0087)	(0.0058)	(0.0077)	(0.0065)	(0.0091)
Single Plant (Reference Category)					
Headquarter	-0.0165***	0.0072*	-0.0277***	0.0237***	0.0042
	(0.0061)	(0.0043)	(0.0056)	(0.0049)	(0.0066)
Branch Plant	-0.0846***	0.0177***	-0.0455***	0.0578***	0.0507***
	(0.0061)	(0.0042)	(0.0056)	(0.0047)	(0.0065)
Collective Bargaining Agreement	0.0328***	-0.0346***	0.0506***	-0.0219***	-0.0575***
	(0.0041)	(0.0030)	(0.0040)	(0.0033)	(0.0045)
Log. Labour Productivity	-0.0374***	0.0541***	-0.0234***	0.0333***	0.0846***
	(0.0022)	(0.0018)	(0.0022)	(0.0019)	(0.0026)
Working Owner	-0.0096**	0.0005	0.0048	0.0134***	0.0013
	(0.0042)	(0.0029)	(0.0042)	(0.0032)	(0.0045)
Firm Age	-0.0020***	0.0001	-0.0008***	0.0005***	0.0005*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Foreign Ownership	-0.0073	0.0234***	-0.0372***	0.0149***	0.0406***
	(0.0083)	(0.0048)	(0.0058)	(0.0057)	(0.0082)
Industry Dummes (9)	Yes***	Yes***	Yes***	Yes***	Yes***
Year Dummies (15)	Yes	Yes	Yes	Yes	Yes
Firm Size Dummies (5)	Yes	Yes	Yes	Yes	Yes
Constant	1.5473***	0.7039***	1.2430***	0.6492***	0.7053***
	(0.0140)	(0.0125)	(0.0232)	(0.0126)	(0.0181)
No. of Obs.	74500	74500	74500	74500	74500
No. of Clusters	21297.00	21297.00	21297.00	21297.00	21297.00
F-Stat	352.29	162.37	314.43	233.22	153.04
R squared	0.39	0.22	0.42	0.29	0.21

Note: Cluster-Robust standard errors in parentheses: p<0.10, ** p<0.05, *** p<0.01; Dummy variables contain, firm size classes, industry classification, and year. Source: LIAB QM 9310, own calculations.

Here, we can see mostly similar patterns. Offshoring firms have less routine manual jobs before the offshoring takes place, while the shares of the other job tasks are higher. After the offshoring takes place, these firms still have higher non-routine interactive and non-routine analytic job task shares. However, there are differences in the types of job tasks that are offshored, as compared to all mass lay-offs. Offshoring firms differ overall less in terms job task shares compared to non-offshoring firms after the offshoring takes place, in comparison as they did before. This means that offshoring firms are a special selection of less manual-focused firms before they offshore, but they mainly lose this treat during the process.

5 Conclusion

The results show that firms that perform mass lay-offs to offshore parts of the production process have higher share of non-routine interactive jobs. After a mass lay-off has taken place, they have higher shares of routine cognitive and non-routine interactive jobs. During the process, they mostly shed both routine and non-routine manual jobs.

Our results indicate that firms that offshore parts of the production employ less productive jobs before the mass lay-off takes place. After the mass lay-offs they are less similar to other firms. A possible explanation could be taken from the theoretical model by Skaksen (2004), which states that collective bargaining could allow these firms to be more productive through paying lower wages as a *threat of offshoring* effect. After the offshoring takes place, unions press for higher wages, such that the firms are forced to let go additional manual jobs.

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Appendix

To be filled with tables.