Labour Market Polarisation and Monopsony Power

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Abstract

Using a semi-structural approach based on a dynamic model of new monopsony as well as survival analysis, we examine to what extent workers performing different job tasks are exposed to different degrees of monopsony power, and whether these differences in monopsony power have changed over the last 30 years. We find that workers performing mostly non-routine job tasks are exposed to a higher degree of monopsony power than workers performing routine tasks. This indicates that task-specific human capital is important for explaining level differences between worker groups; however, technological change does not seem to have affected the evolution of monopsony power over time.

JEL codes: *J24; J42; J62*

Keywords: *monopsony; labour-supply elasticities; technological change; task approach; routine intensity*

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1 Introduction

The labour market effects of technological change through digitalisation and the increased use of robots and artificial intelligence have raised major concerns amongst the public, politicians, and academic economists in recent years. Indeed, workers performing jobs with a high degree of routine task intensity (RTI) are most at risk because their jobs are relatively easily substitutable by computers and robots; as a result, routine employment has strongly fallen over the past decades, both in Europe and in the US (Goos, Manning, and Salomons, 2009; Autor, Levy, and Murnane, 2003; Autor and Dorn, 2013). As routine jobs are concentrated in the middle of the wage distribution, this trend has led to labour market polarisation in terms of employment. However, it remains unclear whether – and if so, how – technological change and the ensuing polarisation of the labour market have changed the wage-setting power of employers, i.e., monopsony power. This is important because monopsony power is a crucial determinant of wages and therefore of workers' welfare. Furthermore, the degree of monopsony power determines the effects of labour market policies such as the minimum wage (Bachmann and Frings, 2017; Card and Krueger, 1994; Neumark and Wascher, 2008).

In this paper, we therefore investigate the link between RTI and the degree of monopsony power. We do so by answering three research questions. First, are workers whose jobs differ with respect to RTI exposed to different degrees of monopsony power? Second, how did the degree of monopsony power evolve over time for workers performing jobs with different levels of RTI? Third, which factors can explain the differences in terms of monopsony power between workers performing jobs with different levels of RTI? We thus contribute to the literature on monopsony power by providing the first evidence on the relation between the task content of jobs and the market power of employers, both in a cross-sectional setting and over time.

From a theoretical point of view, the cross-sectional differences of monopsony power between workers performing jobs with different levels of RTI are not clear-cut. As discussed in more detail in the next section, monopsony power has several sources, including job-specific human capital, search frictions (mainly through information imperfections), costs of regional mobility, and preferences for non-pecuniary factors such as working environment or flexible working time. As the importance of these factors is likely to differ between workers performing jobs with different levels of RTI, the relation between RTI of a specific job and the degree of monopsony power ultimately boils down to an empirical question.

Furthermore, the differences in monopsony power by routine intensity could have changed over time, especially as job opportunities have declined for workers with highly routine jobs in industrialized countries during the last decades (Cortes, 2016; Goos, Manning, and Salomons, 2014). A decline in job opportunities, i.e. lower labour demand, has been shown in a business-cycle context to increase the degree of monopsonistic competition (Depew and Sørensen, 2013; Hirsch, Jahn, and Schnabel, 2018; Webber, 2018). Given the decline in job opportunities of workers performing highly routine jobs, one could therefore expect higher monopsony power towards theses workers over time.

In order to empirically answer our three research questions, we use the semi-structural estimation method proposed by Manning (2003a) which has been applied frequently in the literature to assess the degree of monopsony power for heterogeneous groups of workers. This approach allows us to identify the wage elasticity of labour supply to the firm, with low wage elasticities indicating a high degree of monopsony power.[1] Our analysis is based on two unique data sets from Germany. On the one hand, we use administrative data on individual labour market histories spanning the time period 1985 – 2014. This data set includes a number of socio-demographic worker characteristics as well as firm characteristics, and is particularly well suited to identify labour market transitions, including job-to-job transitions. On the other hand, we use survey data that contains time-varying information on individual job tasks. From this data set, we compute the task intensity at the occupational level, which we merge to the administrative data set.

We apply two approaches to determine the task content each worker performs in his job. First, we follow the international literature on labour market polarisation which differentiates between relatively broad task groups (see e.g. Goos and Manning, 2007; Goos, Manning, and Salomons, 2009; Cortes, 2016). In order to facilitate the comparability of our results with this well-established literature, we estimate the wage elasticity separately for task groups, in our case routine, non-routine cognitive (NRC), and non-routine manual (NRM) workers. A disadvantage of this classification of workers via occupations into task groups is that it is rather broad, and fixed over the entire observation period. As a second approach, we therefore combine the administrative data set on labour-market histories with the survey data set on job tasks, thus including a continuous measure of RTI as an explanatory variable as in Bachmann, Cim, and Green (forthcoming). In contrast to the first approach, we are therefore able to employ a time-varying task intensity measure for a relatively large number of occupational groups. This time-varying task intensity measure mitigates potential measurement errors due to changing occupational task contents over time. Furthermore, this approach allows us to quantify the importance of RTI for differences in monopsony power between workers.

Our analysis is also closely related to the recent literature on routine-biased technological change (RBTC) and worker flows. Cortes and Gallipoli (2017), using data from the Current Population Survey (CPS) and the Dictionary of Occupational Titles (DOT), examine the importance of task distance between occupations (as in Gathmann and Schönberg, 2010) for the corresponding worker flows in the US. They show that for most occupation pairs, task-specific costs account for up to 15% of the costs that arise when individuals move between occupations. Bachmann, Cim, and Green (forthcoming) analyse the link between labour market transitions and job tasks for the German labour market. They find differences in the mobility patterns of

[1]See Sokolova and Sørensen (2018) for a recent meta-analysis of studies on labour market monopsony.

workers belonging to different task groups, and that RTI plays an important role for worker mobility.

Our results can be summarised as follows: First, workers with high RTI display a higher wage elasticity of labour supply to the firm than workers with low RTI, indicating that workers with low RTI are subject to higher monopsony power by employers. An analysis of the components of this wage elasticity shows that for a given decline in wages, workers with low RTI are less likely to separate to employment or non-employment, and they are less likely to be recruited from employment than non-employment compared to workers with high RTI. The most likely explanation for this result is that workers with low RTI (especially NRC workers) dispose of more job-specific human capital and that they assign a higher importance to non-pecuniary benefits from their job than workers performing jobs with higher RTI. Second, the differences in monopsony power between workers performing jobs with low RTI and workers performing jobs with high RTI stay relatively constant over time, and we do not find pronounced long-run trends for any worker group. This can be seen as an indication that the polarisation of the labour market has not increased monopsony power over time. Finally, we find that labour market thickness, measured by the type of region where a job is located, and collective bargaining coverage matter for the overall degree of monopsony power of the labour market, but cannot explain differences between workers performing jobs with different levels of RTI.

The contribution of our paper is thus three-fold: First, we are the first to provide evidence on the link between job tasks and monopsonistic competition in general, and especially to quantify the importance of RTI in this context. This is particularly relevant because technological change, through the increased use of artificial intelligence, is expected to have a major impact on labour markets in the future. Second, we show to what extent RTI contributes to changes in the degree of monopsonistic competition over a long time period using a time-varying measure of RTI. Third, our analysis provides evidence on one potential channel for minimum wage effects. The higher wage elasticity of labour supply to the firm for workers with high RTI implies that these workers are closer to the perfect competition scenario in which minimum wages lead to an unambiguous decline in jobs. Therefore, our results provide a potential explanation for recent findings from the US that minimum wage increases have had more negative employment effects for workers whose jobs are more easily automatable (Lordan and Neumark, 2018).

2 Task Groups, Technological Progress, and Employers' Monopsony Power

In the following, we discuss theoretical arguments for potential differences in the monopsony power faced by workers performing different job tasks and how these differences may have changed over time because of technological progress. We start our discussion with the potential sources of monopsony power and explore how the importance of these sources may vary according to workers' job tasks. In a second step, we discuss how the link between job tasks and monopsony power may have changed over time.

For ease of exposition, we follow Cortes (2016) and distinguish three different task categories:

1. Routine: Administrative support, operatives, maintenance and repair occupations, production and transportation occupations (among others).
2. Non-Routine Cognitive (NRC): Professional, technical management, business and financial occupations.
3. Non-Routine Manual (NRM): Service workers.

The potential sources of monopsony power in general are identified in the literature to be specific human capital (Webber, 2015), search frictions, mobility costs, and non-wage preferences (Manning, 2003a). For the purpose of this paper, some of these sources can serve as an explanation for differences in monopsony power between workers performing different tasks. Production technology and technological progress may play a role in this context, but differences may also arise through factors unrelated to technology. In the remainder of this section, we discuss the sources of monopsony power and how they are linked to production technology and technological progress. We start with the different sources of monopsony power, which could potentially explain cross-sectional differences between task groups.

The first source of monopsony power, job-specific human capital, implies that a job change leads to a loss of human capital. The existence of job-specific human capital therefore decreases workers' incentives to switch jobs in order to improve their wage, i.e. it increases monopsony power of employers. Importantly for our purpose, we regard job-specific human capital to be related to job tasks (Gathmann and Schönberg, 2010): If the tasks in the new job are very different from the old one, task-specific human capital gets lost. As the transferability of human capital is likely to differ between task groups (see below), this implies that this source of monopsony power can potentially explain differences in the monopsony power of employers between task groups.

More specifically, this source of monopsony power can be expected to be important for differences between task groups because the production of output generally requires the combination of tasks into task bundles and because more highly-skilled workers can perform more complex tasks. For example, in the Ricardian model of the labour market of Acemoglu and Autor (2011), the unique final good is produced by combining a continuum of tasks with three factors of production: high-, medium- and low-skilled workers. Each task can be performed by every skill type, but the comparative advantage of skill types differs across tasks.

Thus, more complex tasks can be better performed by high-skill workers than medium-skill workers, while intermediate tasks can be better performed by medium-skill workers than low-skill workers. Furthermore, it will cost strictly less to perform simpler tasks with low-skill rather than medium-skill or high-skill workers. As a result, more complex tasks are performed by high-skill workers, less complex tasks by low-skill workers (Acemoglu and Autor, 2011).

A similar set-up can be used to take into account that task bundles can also be formed by combining different types of workers. For example, in the model of Booth and Zoega (2008), the range of tasks any firm can perform is determined by the collective ability of its entire workforce. Therefore, worker heterogeneity translates into firm heterogeneity when collective abilities within firms are not identical. In this model, only firms characterized by workforces of higher ability can perform complex tasks, and complex tasks can be performed in a smaller number of firms than simpler tasks. As a result, high-skill workers are only able to perform the most complex tasks in the relatively few firms with a very specific workforce, and therefore these workers only have few outside options. Therefore, firms performing complex tasks have high monopsony power towards their workers, particularly the high-skill ones.

The second source of monopsony power, search frictions through information imperfections, leads to higher monopsony power because such frictions imply that workers are less well informed about job opportunities and therefore react less strongly to wage differences (Manning, 2003a). On the one hand, this source can be expected to be less important for NRC workers as these workers are generally high-skilled and therefore better able to acquire information about job opportunities. This will be less so for routine or NRM workers. On the other hand, as pointed out above, non-routine jobs usually imply more complexity in the tasks to be performed. Therefore, non-routine workers can be expected to have greater difficulties in acquiring information about available jobs and their exact requirements in terms of job tasks than routine workers. As a result, routine workers can be expected to face lower monopsony power than non-routine workers. Given these counteracting mechanisms, theory does not offer clear guidance regarding the role of search frictions for cross-sectional differences in monopsony power between task groups.

Third, mobility costs leading to limited regional mobility also increase monopsony power. Higher mobility costs mean that a job change, which is accompanied by a need to switch the place of residence, is less attractive. Searching only in local labour markets, however, reduces the number of available job opportunities and thus makes the worker less responsive to wage differences. Generally, mobility costs - especially in a non-monetary sense - vary between workers, implying different degrees of limited mobility at the worker level. Conditional on these individual differences in limited mobility, the effect of limited mobility on monopsony power may be stronger in less densely populated areas (Manning, 2003b; Hirsch, König, and Möller, 2013). The underlying idea is that the number of job opportunities declines in thinner labour markets, once we assume that workers only search locally.

Applying this general result to differences in monopsony power faced by different task groups, we would not per se expect strong cross-sectional differences in limited mobility between task groups. However, the ongoing structural change and the resulting decline in job opportunities for routine workers implies that local labour markets potentially get thinner for routine workers. On average, we therefore expect the increase in monopsony power in rural compared to urban areas to be stronger for routine workers than for NRC and NRM workers.

Finally, preferences that assign a high weight to non-pecuniary job characteristics such as flexible working times or a pleasant work enviroment also lead to a lower wage-responsiveness of workers and thus to a lower wage elasticity of labour supply to the firm. Generally, Sullivan and To (2014) show that non-wage job characteristics play an important role in job search and argue that, a priori, it is not completely clear in which direction they influence differences between task groups: on the one hand, preferences for non-pecuniary factors can be hypothesised to be more important for NRC workers because this group is generally characterised by higher wages, i.e. the marginal gain from an additional wage increase relative to non-pecuniary aspects is smaller. On the other hand, workplace safety can be regarded as an important non-pecuniary factor for both routine and NRM workers, which would speak for higher monopsony power for these worker groups. However, recent evidence from the US labour market shows that high-wage workers generally enjoy more favourable non-wage job characteristics (Maestas, Mullen, Powell, Von Wachter, and Wenger, 2018). This may speak in favour of workers with higher wages, i.e. NRC workers, assigning a higher weight to non-wage job characteristics.

Differences in monopsony power between task groups may not only arise in the cross-section, but could have changed over time, especially as the general labour market situation of workers belonging to different task groups has evolved very differently in recent decades. There is ample evidence for the US and many European countries that routine work has strongly declined (see e.g. Autor and Dorn, 2013, and Goos, Manning, and Salomons, 2014), and that this has had adverse effects on routine-workers' long-term employment probabilities (see Bachmann, Cim, and Green, forthcoming, for Germany and Cortes, 2016 for the US), and wages (Cortes, 2016).

These general developments are likely to have affected the evolution of monopsony power in the labour market. The main reason for this is the worsening of job opportunities for routine workers over the last few decades described above. As shown by Depew and Sørensen (2013) and Hirsch, Jahn, and Schnabel (2018) in a business-cycle context, the degree of monopsonistic competition in the labour market increases at times in which labour demand is relatively low. They explain this by workers' job separations being less wage-driven and firms finding it relatively easier to poach workers, as a higher wage increases the probability that a recruit comes from employment, when unemployment rises. Intuitively, a higher unemployment rate leads to a lower incentive of workers to enter the labour market state of unemployment, as frictions in the labour market are higher. Consequently the wage offer is relatively lower in order to persuade workers to take the job instead of entering unemployment first and searching for a better job offer. Therefore, when job opportunities are diminished, search frictions play a more important role, and preferences for job security become more important (Hirsch, Jahn, and Schnabel, 2018).

Extending this argument to a long-run analysis, one could expect that the labour supply elasticity to the firm has decreased for routine workers. This is so because labour market polarisation has led to a reduction of jobs that predominantly perform routine tasks, which means that outside options decreased for this task group. Workers performing routine tasks will therefore be limited in their ability to separate from a job, following a small wage cut, as other job options with their task profile have become rare. Therefore, the labour supply elasticity to the firm for this task group will be less wage driven over time. At the same time, we expect that the labour supply elasticity to the firm for workers performing NRC tasks will probably be more wage driven over time, because labour market polarisation has led to an increase of outside options for this task group. This line of reasoning is consistent with the model by Acemoglu and Restrepo (2018), where technological progress leads to the emergence of new tasks that can be performed best by high-skill workers. This mechanism is likely to have an impact mainly on the role of search frictions for monopsony power, with task-specific human capital playing an important intermediary.

Finally, there exists another long-run trend that could have affected the evolution of monopsony power in the labour market: the rise of superstar firms. As Autor, Dorn, Katz, Patterson, and Van Reenen (2017) point out, technological change and globalization benefit the most productive firms in each industry. This leads to product market concentration as industries become increasingly dominated by superstar firms with high profits and a low share of labour in firm value-added and sales. This increased product market concentration is likely to be accompanied by stronger labour market concentration and thus to lead to monopsony power in the labour market, as shown for the US by Azar, Marinescu, and Steinbaum (2017). Therefore, this long-run trend can be viewed as a change in the composition of firms towards more firms with high monopsony power, which raises overall monopsony power in the labour market.

Summarising, cross-sectional differences between task groups can mainly be expected because of the existence of task-specific human capital and non-wage preferences. While task-specific human capital should lead to a higher degree of monopsony power towards NRC workers, who are mainly high-skilled, the same is true for the impact of non-wage preferences, although for the latter this is less clear from a theoretical point of view. Regarding long-run trends, our theoretical considerations imply that the importance of task-specific human capital has increased for routine workers because their job opportunities have strongly declined.

Furthermore, the rise of superstar firms can be expected to lead to an increase in monopsony power for all task groups.

3 Methodology

We follow Manning (2003a) in estimating the labour supply elasticity to the firm as a measure of the degree of monopsonistic competition. This estimation approach is based on a dynamic monopsony model of the labour market, which in turn heavily draws from the Burdett and Mortensen (1998) equilibrium search model. Assuming that workers leave the firm at a rate $s(w_t)$ that depends negatively on the wage paid, and that recruits arrive at the firm at a rate $R(w_t)$ that depends positively on the wage paid, the labour supply elasticity can be expressed as

$$L_t = R^e(w_t) + R^n(w_t) + [1 - s^e(w_t) - s^n(w_t)]L_{t-1}, \tag{1}$$

with firms paying wage w_t at time $t = 1, 2, \ldots$. The exponents e and n indicate the destination states (for separations) or states of origin (for recruitments) corresponding to employment and non-employment, respectively.

Considering the steady state in which total separations must equal recruits and $L_t \equiv L$ and $w_t \equiv w$, we have

$$L(w) = \frac{R^e(w) + R^n(w)}{s^e(w) + s^n(w)}, \tag{2}$$

which results in positive long-run relationship between employment and wages. Equation 2 implies that the long-term elasticity of labour supply to the individual firm ϵ_{Lw} is the difference of a weighted average between the wage elasticities of recruitment from employment (ϵ^e_{Rw}) and non-employment (ϵ^n_{Rw}), and the wage elasticities of the separation rates to employment (ϵ^e_{sw}) and non-employment (ϵ^n_{sw}), i.e.

$$\epsilon_{Lw} = \theta_R \epsilon^e_{Rw} + (1 - \theta_R)\epsilon^n_{Rw} - \theta_s \epsilon^e_{sw} - (1 - \theta_s)\epsilon^n_{sw} \tag{3}$$

where the weights are given by θ_R, the share of recruits hired from employment, and θ_s, the share of separations to employment.

Estimating the separation rate elasticities using data on job durations is relatively straightforward, but estimating the recruitment elasticities requires information that is typically not available in data sets. Specifically, we do not have information on the firms' applicants and the wages offered to them. A solution is to impose additional structure on the model (see Manning, 2003a, 96-100) by using the Burdett and Mortensen (1998) equilibrium search model with wage posting and assuming a steady state.[2] Note that in a steady state, $\theta \equiv \theta_R = \theta_s$ holds. Imposing this on Equation 3 gives the following relation

$$\epsilon_{Lw} = -(1+\theta)\epsilon_{sw}^{e} - (1-\theta)\epsilon_{sw}^{n} - \epsilon_{\theta w} \tag{4}$$

where $\epsilon_{\theta w}$ is the wage elasticity of the share of recruits hired from employment and θ is the overall share of hires from employment. This estimation approach is widely used in the literature (Hirsch, Schank, and Schnabel, 2010; Booth and Katic, 2011; Hirsch and Jahn, 2015; Hirsch, Jahn, and Schnabel, 2018). Thus, in order to arrive at the labour supply elasticity to the firm, the following components have to be separately estimated and inserted in Equation 4: (i) the wage elasticity of the separation rate to employment, (ii) the wage elasticity of the separation rate to non-employment, (iii) the wage elasticity of the share of recruits hired from employment and (iv) the share of hires from employment.

To estimate the separation rate elasticities to employment and non-employment, we model the instantaneous separation rate of employment spell i at duration time t as a Cox proportional hazard model:

$$s_i^{\rho}\Big(t, x_i^{\rho}(t)\Big) = h_0(t)\, exp\Big(x_i^{\rho}(t)'\beta^{\rho}\Big), \tag{5}$$

where $\rho = e, n$ indicates a separation to employment or non-employment respectively, $h_0(t)$ is a baseline hazard with no assumptions on its shape, $x_i^{\rho}(t)$ is a vector of time-varying covariates with β^{ρ} as a corresponding vector of coefficients.[3] $x_i^{\rho}(t)$ includes log wage as our key independent variable as well as worker, firm and further controls.

Estimating Cox proportional hazard models, which place no restrictions on the baseline hazard, forces us to control for job tenure. There are arguments for and against the inclusion of job tenure. On the one hand, Manning (2003a, 103) argues that including tenure reduces the estimated wage elasticity as high-tenure workers are less likely to leave the firm and are more likely to have high wages. Thus, tenure is itself partly determined by wages, and including it would take away variation from wages and therefore bias the estimated wage elasticity (see also Hirsch, Schank, and Schnabel, 2010; Booth and Katic, 2011; Hirsch,

[2] The key assumption of Burdett and Mortensen (1998) is that wages are posted by firms, and workers simply decide on whether to accept or decline a wage offer. In line with this assumption, Brenzel, Gartner, and Schnabel (2014) showed that wage posting is the predominant mode of wage determination in Germany.

[3] We follow Manning (2003a, 100-101) and assume that, conditional on x, the two types of separations are independent. Thus, one can estimate the separation rates separately. To estimate the elasticity of separations to non-employment, we use the whole sample (all jobs). We only use those jobs that do not end in non-employment when estimating the separation rate to employment.

Jahn, and Schnabel, 2018). On the other hand, considering the existence of seniority wage scales, Manning (2003a) also argued that the exclusion of job tenure would lead to a spurious relationship between wages and separations. The empirical literature on seniority wage schedules in the German labour market suggests that controlling for tenure is appropriate in our application (see e.g. Zwick, 2011, 2012).

We model the probability that a worker is hired from employment (as opposed to non-employment) as a logit model to arrive at an estimate of the wage elasticity of the share of recruits hired from employment $\epsilon_{\theta w}$

$$Pr[y_i = 1|x_i] = \Lambda\Big(x_i'\beta\Big), \tag{6}$$

where the dependent variable is a dummy, which takes the value 1 if it is a recruit from employment and 0 if the recruit comes from non-employment. Λ denotes the cumulative distribution function of the standard logistic distribution. Again, our key independent variable in this equation is the log wage. The coefficient of the log wage in this model gives the wage elasticity of the share of recruits hired from employment $\epsilon_{\theta w}$ divided by $1 - \theta$. Multiplying the coefficient by $1 - \theta$ yields the estimate of $\epsilon_{\theta w}$ in Equation 4. To obtain the weights used in Equation 4, we simply calculate the share of hires θ coming from employment from the data.

In order to analyse differences in the wage elasticity of labour supply to the firm between workers performing different job tasks, we proceed in two ways. First, we estimate the respective wage elasticities separately by task group, using the task classification of Cortes (2016), which is fixed over time. This allows a direct comparison with the US literature using this type of classification. Second, we use a time-varying measure of RTI, which we explain in detail in Section 4. Here, we include the interaction of the log wage and $RTI_i(t)$ to estimate the separation rate elasticities in Equation 5. The respective separation rate elasticity is given by $\epsilon^{\rho}_{sw} = \beta^{\rho}_{w} + \beta^{\rho}_{RTI\times w} \times RTI_i(t)$. Similarly, the wage elasticity of the share of recruits hired from employment, $\epsilon_{\theta w}$, is given by $\beta_w + \beta_{RTI\times w} \times RTI_i(t)$ divided by $1-\theta$. As this second approach allows us to exactly quantify the link between RTI and monopsony power, and because it allows us to control for changes in RTI by occupation over time, this is our preferred approach in the empirical analyses in Section 5.

4 Data

This study uses the weakly anonymous Sample of Integrated Labour Market Biographies (SIAB; 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

Table 1: Sample Description

	Routine		NRM		NRC		All workers	
	Mean	sd	Mean	sd	Mean	sd	Mean	sd
Log(Daily Wage)	4.33	0.34	4.13	0.41	4.59	0.39	4.36	0.39
Share of high-skill workers in firm	6.21	9.60	5.65	8.40	20.32	21.61	9.69	14.91
Share of low-skill workers in firm	17.02	14.43	20.10	15.79	12.65	12.34	16.43	14.39
Share of foreign workers in firm	9.95	13.92	13.57	17.18	7.94	12.64	10.05	14.34
Share of female workers in firm	21.46	19.15	29.95	23.03	35.77	22.89	26.54	21.75
Share in small firms (0-19 employees)	24.89		19.19		19.57		22.57	
Share in medium firms (20-250 employees)	41.88		46.15		38.23		41.68	
Share in large firms (251-999 employees)	17.72		18.37		20.57		18.55	
Share in very large firms (1000+ employees)	14.90		15.69		21.16		16.62	
Missing	0.62		0.60		0.47		0.58	
Share in agriculture and forestry	0.20		0.17		0.10		0.17	
Share in fishery	0.01		0.00		0.00		0.01	
Share in mining industry	1.36		0.30		0.33		0.92	
Share in manufacturing industry	41.96		29.19		29.37		36.59	
Share in energy and water supply industry	1.44		0.29		1.11		1.16	
Share in construction industry	17.54		3.41		2.62		11.34	
Share in trade and repair industry	13.57		17.34		12.00		13.81	
Share in catering industry	0.46		4.48		4.63		2.20	
Share in transport and news industry	7.72		10.32		2.73		6.90	
Share in finance and insurance industry	0.61		0.32		9.64		2.85	
Share in economic services industry	7.50		19.59		17.64		12.13	
Share in public services industry	3.98		4.08		3.70		3.93	
Share in education industry	0.43		1.05		3.67		1.36	
Share in health industry	0.80		4.57		7.57		3.16	
Share in other industry	1.80		4.27		4.41		2.88	
Missing	0.63		0.61		0.48		0.58	
Share in top 3 industries with highest collective bargaining commitment	22.13		7.82		15.95		18.13	
Share in bottom 3 industries with lowest collective bargaining commitment	21.74		32.14		19.36		22.91	
Share of foreign workers	11.70		19.01		6.46		11.62	
Share without vocational training	10.94		20.42		2.21		10.34	
Share with upper secondary school leaving certificate or vocational training	83.91		73.34		61.75		76.49	
Share with university degree or university of applied sciences degree	2.88		1.82		33.64		10.50	
Missing	2.28		4.42		2.40		2.67	
Share in age group 18-25	15.49		18.74		8.13		14.18	
Share in age group 26-35	30.11		31.63		33.55		31.24	
Share in age group 36-45	28.95		27.42		32.96		29.71	
Share in age group 46-55	25.45		22.21		25.36		24.88	
Share in district-free cities	30.20		36.25		44.11		34.76	
Share in urban districts	44.13		42.76		39.03		42.60	
Share in rural districts, some densely populated areas	14.14		12.18		9.54		12.64	
Share in rural districts, sparsely populated	10.90		8.20		6.84		9.41	
Missing	0.62		0.60		0.47		0.58	
Number of separations to employment	270,344		89,636		120,606		480,586	
Number of separations to non-employment	488,078		189,879		160,533		838,493	
Number of employment spells	4,190,015		1,240,511		1,845,847		7,276,376	

Notes: Employment spells are split by calendar year. Shares are expressed in percent.
Source: SIAB and BHP, 1985-2014. Authors' calculations.

access. We combine this data with the Establishment History Panel (BHP), also provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

The SIAB is a representative 2% random sample of the Integrated Employment Biographies (IEB) that contains the labour market history of all individuals in Germany who are employed subject to social security contributions, those in part-time employment not earning enough to make social security contributions, those receiving unemployment or social benefits, and those officially registered as job-seeking at the German Federal Employment Agency or participating in programs of active labour market policies. Civil servants and self-employed workers are not included in the data. The information on labour market states is exact to the day. The main worker-level characteristics contained in the data are workers' education, age, nationality, and occupation. A detailed description of the Sample of Integrated Labour Market Biographies is provided in Antoni, Ganzer, and vom Berge (2016).

The data furthermore allow us to identify different labour market states at the individual level. We follow the theoretical model based on Manning (2003a) and distinguish between the two labour market states, employment and non-employment. Therefore, a job may end with a separation to employment or non-employment. The administrative data builds on both establishments' reports of a new employee and individuals' notifications of moving into or out of unemployment. These reports and notifications are not always exactly consistent with the actual change of labour market state. For example, workers might report to the unemployment office only a few days after they are laid off.

We deal with these potential measurement errors in the following way: If the time gap between two employment spells at different establishments (i.e., an establishment with a different establishment identifier) does not exceed 30 days, this is defined as a separation to employment. If the time gap between two employment spells at different establishments exceeded 30 days, we defined this time gap as a non-employment spell. A separation to non-employment is also defined as a job spell ending in registered unemployment or no spell in the data at all. Further, we take care of recalls in the following way: Recalls are defined as one single employment spell if the time gap between two employment notifications at the same firm does not exceed 120 days. If the time gap between two employment notifications at the same firm is equal to or larger than 120 days, we defined this gap as an additional non-employment spell. Treating recalls as continuous employment spells ensures that seasonal effects that differ among industries and task groups and may affect wages and transitions into/from non-employment simultaneously do not distort the results.

In our empirical analysis, we focus on the core labour force in dependent employment and therefore exclude apprentices, trainees, homeworkers, and individuals older than 55. We further restrict our analysis to male workers in order to avoid selectivity issues regarding female labour force participation. The SIAB provides information on workers' employment biographies from 1975 onwards. However, the wage variable does not include bonus payments before 1985 but does so afterwards. Therefore, we do not use pre-1985 wage information in our analysis and restrict our observation period to 1985-2014. As our observation period includes the pre-unification period, we focus on West Germany only. Including observations for East German workers from 1992 onwards and therefore restricting our analysis to the post-unification period would considerably reduce our period of observation and thus the long time period needed to properly answer our research questions. The SIAB data provides highly reliable information on the daily wage of every spell, but no information on working hours is available. We therefore focus on full-time workers, as this ensures comparability between daily wage rates. Wages are right-censored at the social security contribution limit. To avoid possible biases in the estimated wage elasticity of labour supply, we exclude all job spells with wages that are at this limit at least once during the observation period. Information on workers' education is provided by employers and is therefore inconsistent or missing for some workers. To correct for the inconsistent education information, we impute the missing information on workers' education by using the procedure proposed by Fitzenberger, Osikominu, and Völter (2006).

The Establishment History Panel (BHP) provides information on establishment characteristics such as worker group shares with respect to skill, gender, part-time employment and nationality, as well as the establishment size and the average age of its workforce. Furthermore, it is possible to identify plant closures (Hethey and Schmieder, 2010). We therefore exclude plants during their closing year, thus focusing on voluntary, supply-side driven separations from a job. Excluding plants in their closing year helps to mitigate the possible spurious relationship between wages and separations that is not driven by workers' labour supply behaviour.

In order to compute routine task intensity (RTI), we use the BIBB/IAB and BIBB/BAuA Employment Surveys (herein BIBB data) that provide a representative sample of German workers and include questions regarding the task content of jobs. These data have been used by, among others, Antonczyk, Fitzenberger, and Leuschner (2009), and Baumgarten (2015) to generate measures of relative task intensity at the occupational level. We follow the approach of Antonczyk, Fitzenberger, and Leuschner (2009) and categorize the activities employees perform at the workplace into routine (R), non-routine cognitive (NRC) and non-routine manual tasks (NRM) to measure different task intensities at the individual level. We aggregate these individual task intensities for 54 occupational categories following Tiemann, Schade, Helmrich, Hall, Braun, and Bott (2008), and for each occupation-time period combination provide a R, NRC and NRM share that sums to 100%.[4] The ensuing RTI measure can be expressed as

[4] Using a finer occupational classification is not possible given the relatively small sample size of the BIBB

$$RTI_{it} = \frac{\text{number of routine activities performed by i in cross section t}}{\text{total number of activities performed by i over all categories at time t}} \tag{7}$$

Taking the averages of individual routine task intensities provides a continuous measure of RTI over time for a given occupational group. The RTI measure can easily be merged to the worker-level SIAB data.

A key advantage of these data is that the survey is conducted at regular six to seven year intervals throughout our period of analysis (1985/86, 1991/92, 1998/99, 2006 and 2012). This allows us to have time-varying task intensity by occupational groups. Our main approach is therefore to fully exploit the BIBB data to update occupation task intensities over time. This has the advantage that worker outcomes are evaluated more closely to their actual task composition at the time of observation. Thus, computing task intensities with the usage of additional data sources is in contrast to the more parsimonious approach, which assigns workers to routine, non-routine manual and non-routine cognitive categories at one point in time based on groups of standardised occupational codes (see e.g. Goos and Manning, 2007; Goos, Manning, and Salomons, 2009; Cortes, 2016). A cost of relying on occupational task analysis with the BIBB data is that, when compared to using initial task values only, there is the potential of marked discontinuities in the task intensity shares at BIBB survey dates. However, as shown by Bachmann, Cim, and Green (forthcoming), these are not large in terms of continuous measures of task intensity. The mean of our RTI measure for the whole sample amounts to 0.368 with a standard deviation of 0.164.

Table 1 gives an overview on our final sample. Our final sample consists of 7,276,376 employment spells with 480,586 separations to employment and 838,493 separations to non-employment. The descriptive evidence is in line with the expectations and show that NRM workers are in the lower, routine workers in the middle and NRC workers in the higher end of the wage and skill distribution (see e.g. Acemoglu and Autor, 2011; Cortes, 2016). The share of foreign workers among all NRM workers is relatively high compared to the other task groups. NRM workers are also more likely to work with foreign workers and low-skill workers in their respective firms, while NRC workers have more high-skilled co-workers. In comparison to the other task groups, a high share of routine workers are in small firms and a distinctively high share of routine workers work in the manufacturing industry, while a large share of NRC workers are in very large firms. A relatively high share of NRC workers work in district-free cities. A high share of routine workers work in urban districts, but in comparison to the other task groups are also relatively likely to work in rural districts.

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data.

5 Results

5.1 Monopsony power by task groups

We begin our empirical analysis with the first approach described in Section 3, i.e. we estimate the labour supply elasticities to the firm for three task groups, routine, NRC and NRM workers, and we do so for the whole observation period. Thus, we estimate Cox models for the separation rates to employment and non-employment and logit models for the probability that a worker is hired from employment (as opposed to non-employment) separately for these three groups. Our key independent variable in each of these estimations is the log wage. Inserting the estimated wage elasticities from these models as well as the share of hires from employment into Equation 4 yields estimates of the firm-level labour supply elasticity.

The results for the firm-level labour supply elasticity in Table 2 show that it is distinctly smaller for NRC workers (0.852) than for the other task groups (1.184 and 1.112 for routine and NRM workers, respectively), which implies a higher degree of monopsony power towards NRC workers. Looking at the components of the firm-level labour supply elasticity, we observe that both separation rate elasticities are smaller in absolute size for NRC than for routine workers, thereby leading to the lower labour supply elasticity (compare with Equation 4). This result implies that specific human capital and non-pecuniary factors are important drivers in the separation decision of NRC workers. The estimated wage elasticity of the share of recruits hired from employment reflects that paying a higher wage raises the share of recruits hired from employment to a greater extent for NRC workers than for the other task groups.

In order to shed more light on the mechanisms behind this last result, Figure 1 displays the recruitment rates from employment and non-employment for the time period 1985-2014 separately for the whole sample and each task group. In line with Bachmann and Bechara (forthcoming), the recruitment flow from employment as well as the recruitment flow from employment relative to the recruitment flow from non-employment (EE/NE) is procyclical.[5] Furthermore, no apparent long-run trend seems to exist. The differences in levels of the recruitment rates between task groups show that the labour market is most dynamic for NRM workers, and least dynamic for NRC workers.

For our purpose, the relative size of the recruitment flow from employment in comparison to the recruitment flow from non-employment is of most interest, because this relation is directly influenced by the wage elasticity of the hiring probability from employment. For NRC workers, the recruitment flow from employment is only about a third lower than the recruitment flow from non-employment. In contrast, the recruitment flow from employment for routine workers is only about half the size of the recruitment flow from non-employment. For NRM workers, this fraction is even lower. Stated differently, it is much more

[5] Recessionary periods started in 1992, 2001 and 2008.

Table 2: The Labour Supply Elasticity to the Firm by Task Group and RTI

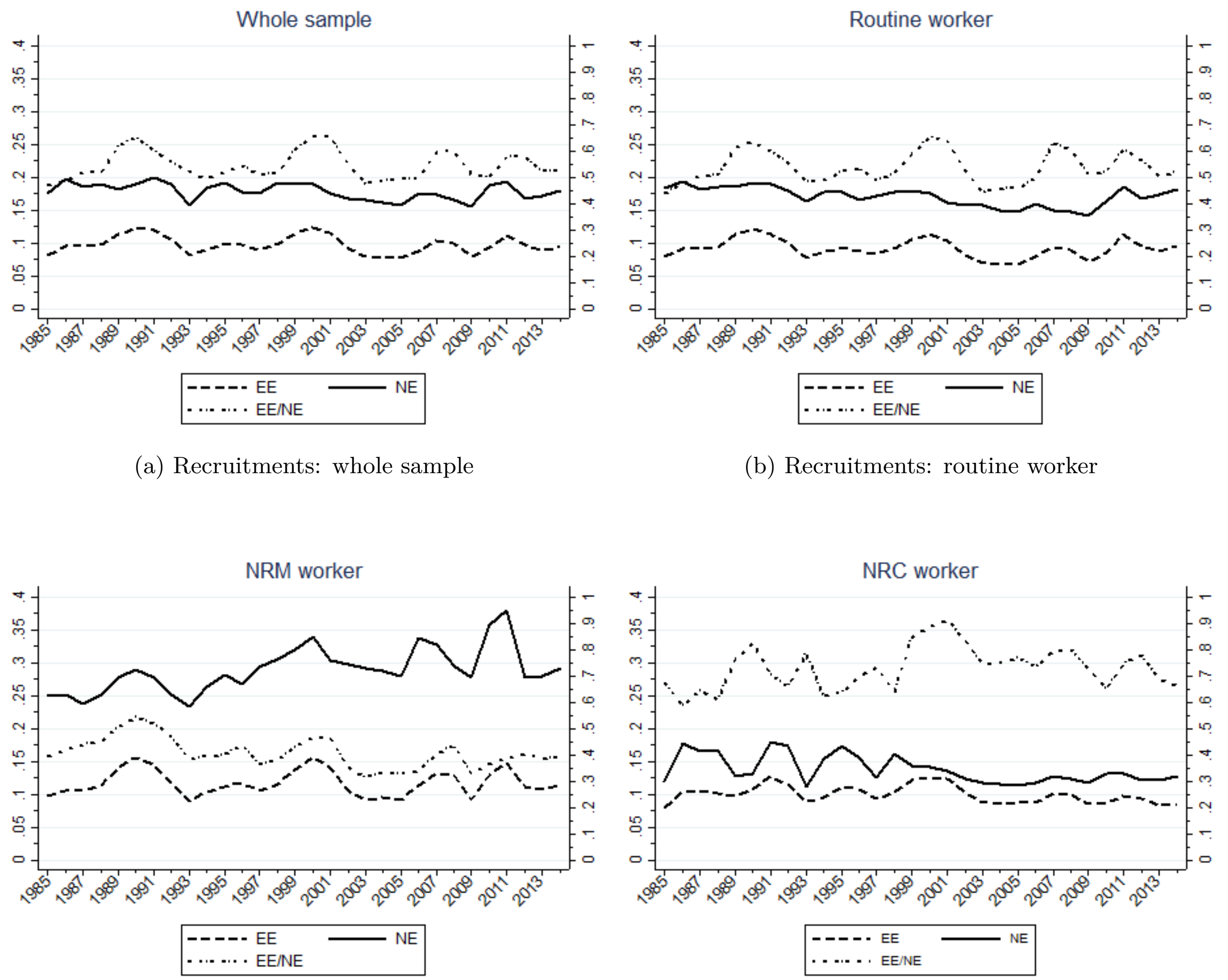
	Routine	*NRM*	*NRC*	*All workers*
Separation rate to employment				
log wage	-1.069***	-0.974***	-0.941***	-1.064***
	(0.009)	(0.016)	(0.014)	(0.007)
log wage × RTI	-	-	-	-0.199***
	-	-	-	(0.005)
Separation rate to non-employment				
log wage	-1.359***	-1.356***	-1.242***	-1.342***
	(0.006)	(0.010)	(0.009)	(0.005)
log wage × RTI	-	-	-	-0.142***
	-	-	-	(0.003)
Hiring probability from employment				
log wage	1.793***	1.574***	2.133***	1.821***
	(0.011)	(0.017)	(0.018)	(0.008)
log wage × RTI	-	-	-	-0.179***
	-	-	-	(0.007)
Share of hires from employment	0.365	0.299	0.438	0.368
Firm-level labour supply elasticity	1.184	1.112	0.852	1.153
for workers with low RTI	-	-	-	0.677
for workers with high RTI	-	-	-	1.628

Notes: Clustered standard errors at the person level in parentheses. RTI is standardized with mean zero and standard deviation one. Thus, workers with low RTI are workers with RTI one standard deviation below the mean, and workers with high RTI are workers with RTI one standard deviation above the mean. The overall labour supply elasticity corresponds to workers with mean RTI. Covariates included in the estimations are education, age, immigrant worker, occupation, sector, year and federal state of the plant controls. Further, we include the shares of low-skilled, high-skilled, female, part-time and immigrant workers in the plant's workforce, plant size, the average age of its workforce and the unemployment rate by year and federal state. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.
Source: SIAB and BHP, 1985-2014. Authors' calculations.

common for firms to recruit from employment when looking for NRC workers than when looking for NRM workers. This may be partly explained by the larger share of NRM workers being in non-employment in the first place (Bachmann, Cim, and Green, forthcoming).

An alternative explanation for the higher recruitments from employment of NRC workers is given by the estimates of the wage elasticity of the hiring probability from employment in Table 2. This elasticity is largest for NRC workers, followed by routine workers, and is lowest for NRM workers. This means that increasing the wage slightly leads to a higher share of recruits coming from employment compared to non-

Figure 1: Recruitment flows



(a) Recruitments: whole sample

(b) Recruitments: routine worker

(c) Recruitments: NRM worker

(d) Recruitments: NRC worker

Notes: EE: Employment-to-employment flows; NE: Non-employment-to-employment flows; EE and NE flows are normalised by the respective employment stock. EE/NE: Employment-to-employment flows relative to non-employment-to-employment flows. Transitions are calculated as described in Section 4.
Source: Authors' calculations based on SIAB 1985-2014, for West Germany.

employment for NRC workers, while this relation is weaker for the other task groups. Note that workers who are hired from employment can be expected to react less strongly to wage differences than workers hired from non-employment. Therefore, the higher wage elasticity of the hiring probability from employment for NRC workers leads to more NRC workers with a low wage response (i.e. employed workers) in the share of recruits, which in turn implies a higher degree of monopsony power towards NRC workers.

Summarising, our results from the approach using three task groups with a fixed classification over time are as follows. First, the lowest wage elasticity of labour supply to the firm, i.e. the highest degree of monopsony power, can be observed for NRC workers. Second, looking at the different components of the wage elasticity of labour supply to the firm, all components contribute to our first result. Third, the recruitment flows over time do not offer an indication for a long-run trend in the mobility behaviour of the different task groups, neither with respect to their level nor with respect to their variability.

5.2 Monopsony power and RTI

In our second estimation approach, we estimate a model including all workers, but we now interact log wages with the routine task intensity (RTI) of each worker. This allows us to study the influence of RTI on the labour supply elasticity to the firm on a continuous scale. More details on RTI are provided in Section 4. Table 2 shows that the results obtained using RTI are in line with those based on separate estimation by task group:[6] While the labour supply elasticity of workers performing jobs with mean RTI equals 1.153, workers with RTI one standard deviation below the mean ("workers with low RTI", e.g. NRC and NRM workers) have a significantly lower labour supply elasticity of 0.677, and workers performing jobs with RTI one standard deviation above the mean ("workers with high RTI", e.g. routine workers) have a significantly higher labour supply elasticity of 1.628. This difference is again driven by all three components of the labour supply elasticity, i.e. the two separation rate elasticities and the elasticity of the hiring probability from employment.

Manning (2003a, 52-53) showed that under monopsonistic wage setting, workers' wage w^m is a fraction of their marginal product ϕ, which directly depends on the labour supply elasticity to the firm

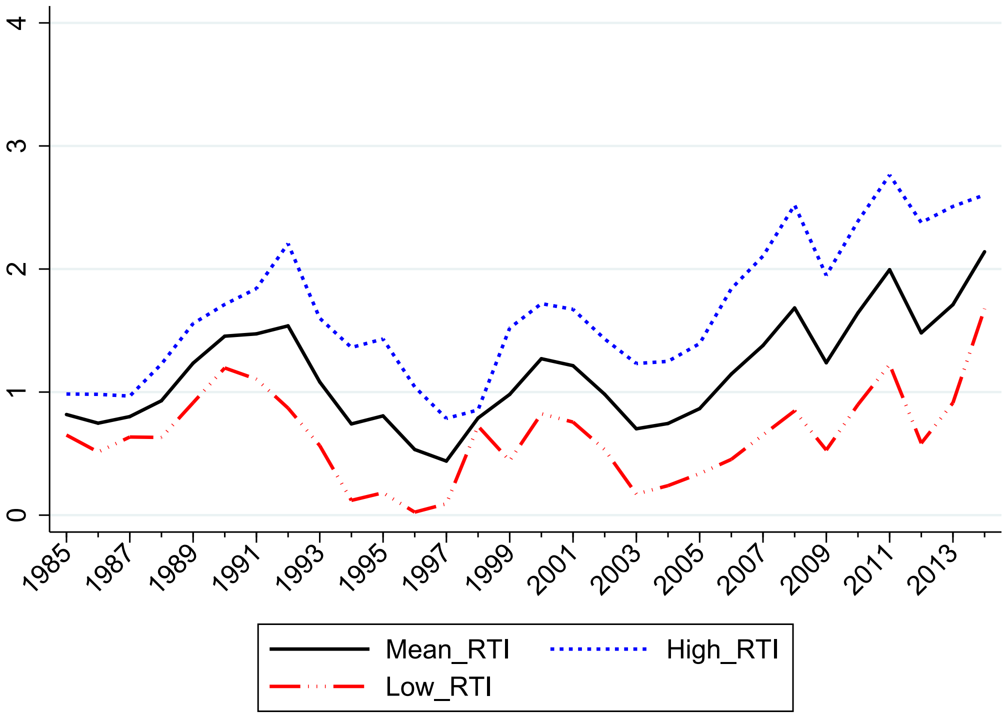
$$w^m = \frac{\epsilon_{Lw}}{\epsilon_{Lw} + 1}\phi. \tag{8}$$

Using this relation and the results of Table 2, we estimate that NRC workers only obtain 46% of their marginal product, which implies a considerable extent of monopsony power facing this task group. Routine workers obtain 54.2% of their marginal product. These differences are even larger when focusing on a continuous measure of RTI: Workers with high RTI receive 62% of their marginal product, while this share only amounts to 40.4% for workers with low RTI.

Given that separate estimations by task groups or interacting wages with RTI both lead to qualitatively similar results, we opt to focus on RTI in the remaining estimations for two reasons. First, RTI is a continuous variable containing more information on the worker's task content. Second, RTI is updated over time, taking into account that the task content of each occupation changes during the observation period, possibly to a different degree (see Section 4).

[6]The full set of regression coefficients can be found in Table A1.

Figure 2: Yearly Labour Supply Elasticities for Workers with Different RTI



Notes: The estimates are derived from the same specification as Column (4) in Table 2. Further, a three-way interaction with year dummies is added to analyse the development over time, i.e. log wages, RTI and year dummies are interacted. The plotted lines correspond to the sum of the relevant coefficients for workers with mean RTI as well as workers with RTI one standard deviation below ("low RTI") and above ("high RTI") the mean.
Source: Authors' calculations based on SIAB 1985-2014, for West Germany.

Next, we turn to the question of the extent to which the estimated labour supply elasticity to the firm changes over time, and if there are differences in this trend by RTI. To do so, we add a three-way interaction to the model using RTI (Column(4) in Table 2). That is, we interact log(wages), RTI and year dummies[7], which allows us to trace the evolution of $log\, wage^{*}RTI$ over time. For ease of interpretation, Figure 2 plots the obtained yearly labour supply elasticities for workers with low, mean, and high RTI. Clearly, the level differences between workers with low and high RTI found for the pooled sample persist, i.e. workers with low RTI have lower yearly labour supply elasticities to the firm compared to workers with high RTI. These differences vary over time, and the labour supply elasticities display a markedly procyclical variation, which confirms the results in Hirsch, Jahn, and Schnabel (2018).

However, cyclical movements in the elasticity of labour supply to the firm appear to be more important

[7]To be complete, we include the base variables (log(wages), RTI, year dummies), the three two-way interactions and the three-way interaction in the model. In deriving the labour supply elasticities shown in Figure 2, we take the sum of the appropriate coefficients.

than long-run trends. There is some indication in Figure 2 that the labour supply elasticity has been increasing from 2003 onwards. However, it would be premature to interpret this rise as a structural shift in labour market competition, as the German labour market experienced no significant downturn during this time period. This rise could therefore simply be due to good economic conditions, which have generally been found to reduce monopsony power (Hirsch, Jahn, and Schnabel, 2018). Even more importantly for our purpose, the increase in the labour supply elasticity is of equal magnitude for workers with low and high RTI. We therefore conclude that labour market polarisation, in terms of decreasing outside options for workers with high RTI, has not influenced the degree of monopsony power faced by routine workers to an important degree.[8]

We provide two robustness checks for the results obtained in Figure 2. First, an alternative choice to estimating labour supply elasticities over time is to use time windows of three years, thereby smoothing the estimates and making them less vulnerable to short-term fluctuations that may exist in yearly estimates. Figure A.1 shows that the general pattern over time is comparable to our yearly estimates, and that differences by RTI appear - if anything - even more pronounced.

Second, up to this point, in our estimations we have used all the variation in wages and transition rates, both across and within workers. Instead, one could estimate stratified Cox models for the separation rate elasticities, in which the baseline hazard $h_{m(i)0}(t)$ is stratified at the worker level, thereby canceling out the worker-specific effect in a similarly convenient way as with the within estimator in linear fixed-effects models (Ridder and Tunalı, 1999).[9] Furthermore, in this robustness test we also use a conditional logit (or fixed-effects logit) model to arrive at an estimate of the wage elasticity of the share of recruits hired from employment.[10] Figure A.2 shows the estimated labour supply elasticities for each year and by RTI using only within-worker variation. There are two important differences: First, all estimated labour supply elasticities are slightly higher and second, differences between workers with low and high RTI are smaller. However, with the exception of one year, workers with low RTI still show lower labour supply elasticities than workers

[8]Theoretically, one could also observe no long-run trend in monopsony power if technological change did have a significant impact that was, however, counterbalanced by one or several other macro factors. However, we do not see an obvious suspect in this context and therefore regard this as an unlikely explanation.

[9]The only difference between the stratified Cox model and the Cox model is that the conventional partial likelihood in the Cox model is based on the conditional probability of exit of an employment spell given that some employment spell in the full sample exits at that time, while the stratified partial likelihood estimator restricts the conditioning to the employment spells in the same unit (worker) at that time. An advantage of the stratified Cox model is that the proportionality assumption inherent to the Cox model needs to hold only for employment spells belonging to the same worker, and may very well be violated across workers without invalidating identification (Kalbfleisch and Prentice, 2011).

[10]We estimate the wage elasticity of the share of recruits hired from employment $\epsilon_{\theta w}$ using the relation $Pr[y_i = 1|x_i, \upsilon_{m(i)}] = \Lambda\Big(x_i'\beta + \upsilon_{m(i)}\Big)$, where $\upsilon_{m(i)}$ is a worker fixed effect. This estimator controls for worker fixed effects by conditioning on those workers who are hired from employment at one point of time and from non-employment at another, and discarding those always hired from the same labour market status.

with high RTI. The general conclusions obtained from using all variation in the data therefore still hold.

Generally, we prefer the estimates based on the Cox model over those obtained from the stratified Cox model for two reasons. First, the stratified Cox model only includes workers in the estimation sample that have at least two employment spells ending in the same transition, which implies that the estimation sample is smaller than the estimation sample of the Cox model without stratification. As workers with different RTI levels could well differ in this respect - e.g. there may be more non-routine workers who display the required transitions - this kind of sample selection is likely to lead to an estimation bias. Therefore, using the entire sample, i.e. estimating without stratification, seems more appropriate. Second, the variation used in the stratified Cox model is purely within-worker variation. Given that workers generally change to jobs with a low task distance (Gathmann and Schönberg, 2010), the within-worker variation in RTI is much smaller than the between-worker variation used in the Cox model without stratification. However, to answer our research questions, comparing workers with different RTI levels seems crucial. Based on these considerations and due to the fact that the results obtained using between-worker and within-worker variations do not differ qualitatively, we analyse the mechanisms potentially driving differences in monopsony power by RTI using the Cox model.

5.3 What can explain the link between monopsony power and RTI?

Having established that workers performing high-RTI jobs face a lower degree of monopsony power than workers performing low-RTI jobs, we explore possible mechanisms behind this finding. As discussed in Section 2, there are several sources of monopsony power. One of the most prominent reasons for monopsony power is that workers do not have a continuous stream of job offers. Therefore, all else equal, workers in labour markets with more firms are more likely to have a greater number of job offers. This effect of labour market thickness on monopsony power may be heterogeneous across workers with different RTI, as labour demand for routine tasks has been decreasing strongly over time (compare with Section 2). We analyze the importance of this mechanism for workers with low and high RTI by running our baseline specification separately for workers situated in different area types. We distinguish between four area types: district-free cities, urban districts, rural districts with some more densely populated areas, and sparsely populated rural areas (BBSR, 2015).

Our results in Table 3 clearly confirm the theoretical expectation for the relationship between labour market thinness and monopsony power: The labour supply elasticity to the firm increases with the urbanity of the district a worker is living in. While the labour supply elasticity of workers with mean RTI amounts to 1.256 in district-free cities, it is reduced to 0.831 in rural districts that are only sparsely populated. However,

Table 3: The Labour Supply Elasticity to the Firm by RTI and Region Type

	District-free cities	Urban districts	Rural districts, some densely populated areas	Rural districts, sparsely populated	Baseline
Separation rate to employment					
log wage	-1.084***	-1.108***	-1.037***	-0.931***	-1.064***
	(0.011)	(0.011)	(0.019)	(0.024)	(0.007)
log wage × RTI	-0.161***	-0.234***	-0.223***	-0.190***	-0.199***
	(0.008)	(0.008)	(0.015)	(0.018)	(0.005)
Separation rate to non-employment					
log wage	-1.367***	-1.379***	-1.281***	-1.242***	-1.342***
	(0.008)	(0.007)	(0.013)	(0.016)	(0.005)
log wage × RTI	-0.113***	-0.173***	-0.153***	-0.133***	-0.142***
	(0.006)	(0.005)	(0.010)	(0.012)	(0.003)
Hiring probability from employment					
log wage	1.756***	1.867***	1.863***	1.848***	1.821***
	(0.013)	(0.013)	(0.024)	(0.028)	(0.008)
log wage × RTI	-0.212***	-0.152***	-0.183***	-0.167***	-0.179***
	(0.011)	(0.010)	(0.019)	(0.023)	(0.007)
Share of hires from employment	0.381	0.373	0.345	0.329	0.368
Firm-level labour supply elasticity	1.256	1.215	1.013	0.831	1.153
for workers with low RTI	0.832	0.690	0.493	0.376	0.677
for workers with high RTI	1.679	1.740	1.533	1.284	1.628

Notes: Clustered standard errors at the person level in parentheses. RTI is standardized with mean zero and standard deviation one. Thus, workers with low RTI are workers with RTI one standard deviation below the mean, and workers with high RTI are workers with RTI one standard deviation above the mean. The overall labour supply elasticity corresponds to workers with mean RTI. Covariates included in the estimations are education, age, immigrant worker, occupation, sector, year and federal state of the plant controls. Further, we include the shares of low-skilled, high-skilled, female, part-time and immigrant workers in the plant's workforce, plant size, the average age of its workforce and the unemployment rate by year and federal state. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.
Source: SIAB and BHP, 1985-2014. Authors' calculations.

the importance of urbanity - as a proxy for labour market thickness - is of similar magnitude for workers with low and high RTI. More specifically, the absolute difference in the labour supply elasticity for workers with low and high RTI is roughly equal to one in all area types. We therefore conclude that while labour market thinness is an important driver of monopsony power in general, workers with different RTI are not affected differently by the reduced number of job opportunities in rural areas.

Another important institutional characteristic of labour markets that potentially influences monopsony power is collective bargaining. More specifically, collective bargaining agreements typically increase wages of low-wage workers and compress the industry's wage distribution. This does not necessarily influence any of the sources of monopsony, but prevents firms from exercising their monopsony power (Manning, 2003a), thereby incrasing the *estimated* labour supply elasticities. Bachmann and Frings (2017) confirm this idea by showing that the estimates of the labour supply elasticity are larger in industries with higher collective bargaining coverage in Germany.

Collective bargaining coverage varies to a large degree at the industry level in Germany. For example,

Table 4: The Labour Supply Elasticity to the Firm by RTI and Collective Bargaining Coverage

	High coverage	Low coverage	Baseline
Separation rate to employment			
log wage	-1.066***	-0.747***	-1.064***
	(0.019)	(0.013)	(0.007)
log wage × RTI	-0.184***	-0.136***	-0.199***
	(0.017)	(0.012)	(0.005)
Separation rate to non-employment			
log wage	-1.367***	-1.082***	-1.342***
	(0.012)	(0.009)	(0.005)
log wage × RTI	-0.042***	-0.124***	-0.142***
	(0.012)	(0.008)	(0.003)
Hiring probability from employment			
log wage	2.094***	1.878***	1.821***
	(0.023)	(0.016)	(0.008)
log wage × RTI	-0.345***	-0.020	-0.179***
	(0.024)	(0.016)	(0.007)
Share of hires from employment	0.347	0.389	0.368
Firm-level labour supply elasticity	0.961	0.551	1.153
for workers with low RTI	0.460	0.275	0.677
for workers with high RTI	1.462	0.829	1.628

Notes: Clustered standard errors at the person level in parentheses. RTI is standardized with mean zero and standard deviation one. Thus, workers with low RTI are workers with RTI one standard deviation below the mean, and workers with high RTI are workers with RTI one standard deviation above the mean. The overall labour supply elasticity corresponds to workers with mean RTI. Covariates included in the estimations are education, age, immigrant worker, occupation, sector, year and federal state of the plant controls. Further, we include the shares of low-skilled, high-skilled, female, part-time and immigrant workers in the plant's workforce, plant size, the average age of its workforce and the unemployment rate by year and federal state. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.
Source: SIAB and BHP, 1985-2014. Authors' calculations.

collective brgaining coverage amounts to 91% in the public services industry and to 37% in transportation and logistics for West Germany in 2016 (WSI, 2018). This might affect our estimates of the labour supply elasticity by RTI in two ways. First, to the extent that workers with low and high RTI are not randomly distributed across industries, these differences might be driving the link between RTI and the labour supply elasticity to the firm. In this case, we should observe much smaller differences in labour supply elasticities by RTI within industries than in the whole sample. Second, differences in monopsony power by RTI might be influenced by collective bargaining coverage at the industry level, because routine workers are much more often low-wage workers compared to non-routine workers. Additionally, due to their public nature, collective bargaining agreements can decrease information asymmetries in terms of wages, but not necessarily in terms of non-wage job characteristics that are not part of the bargaining process. Thus, we expect collective bargaining agreements to increase the labour supply elasticity of routine workers, who are less well informed about wage rates at alternative jobs than non-routine workers (compare with Section 2). In this case, we should observe larger differences in monopsony power by RTI in industries with a low coverage rate of collective bargaining compared to industries with a high coverage rate.

In order to differentiate between these two channels through which collective bargaining coverage influences the estimated labour supply elasticities by RTI, we choose three industries with high[11] and three industries with low[12] collective bargaining coverage, while ensuring that each industry employs workers with varying RTI. We omit industries with average collective bargaining coverage because possible differences in the relationship between RTI and monopsony power will be easier to detect in the tails of the collective bargaining coverage distribution. Also this allows us to neglect changes over time in bargaining coverage. We then run our baseline model for both groups of industries separately.[13]

In line with theoretical expectations, Table 4 shows that the labour supply elasticity to the firm is much lower in industries with a low coverage rate of collective bargaining. Quite importantly, the differences in labour supply elasticities for workers with low and high RTI persist independently of collective bargaining coverage. The labour supply elasticities for workers with mean, low and high RTI all decrease by about 40% when moving from industries with a high coverage rate to industries with a low coverage rate. Our main results are therefore not driven by composition effects in terms of industries. At the same time, we also find no evidence for heterogeneity in the relationship between collective bargaining coverage and monopsony power by RTI.

6 Conclusion

In this paper, we investigate the link between technological change and the degree of monopsony power. We first examine whether workers performing different job tasks are exposed to different degrees of monopsony power. In a second step, we analyse how the degree of monopsony power evolved over time for workers performing different job tasks. Finally, we investigate which factors explain the differences in monopsony

[11]These are the finance and insurance, public services and construction industry with coverage rates of 73%-89%, 83%-91% and 67%-83% in the years 1998-2014 (WSI, 2018), respectively.

[12]These are the trade and repair, transport and news and catering industry with coverage rates of 37%-65%, 38%-61% and 40%-48% in the years 1998-2014 (WSI, 2018), respectively.

[13]The industry variable indicates the economic activity as a 3-digit code and provides time-consistent information. We use the generated time-consistent industry codes in Eberle, Jacobebbinghaus, Ludsteck, and Witter (2011).

power between workers performing different job tasks.

In our analysis, we use the semi-structural estimation approach proposed by Manning (2003a), which allows us to identify the wage elasticity of labour supply to the firm. Our analysis is based on two unique data sets from Germany. First, we use administrative data on individual labour market histories spanning the time period 1985 – 2014. This data set includes a number of socio-demographic worker characteristics as well as firm characteristics, and is particularly well suited to identify labour market flows, including job-to-job, transitions. Second, we obtain time-varying information on individual job tasks from survey data, which allows us to compute the routine task intensity at the occupational level that is merged to the administrative data set. This approach goes beyond many papers in the tasks literature as we are able to measure task content of individual jobs on a continuous scale and account for for changes in job tasks at the occupational level over time.

Our results indicate that workers who perform jobs with lower routine task intensity (RTI) supply labour less elastically to the firm – and thus face higher monopsony power – than workers with higher RTI in their job. The estimated labour supply elasticities equal 0.677 for workers with low RTI and 1.628 for workers with high RTI. Under a simple rule of monopsonistic wage setting, these results imply that workers with low RTI receive only 40.4% of their marginal product, while workers with high RTI receive 62% of their marginal product. The most likely explanation for this result is that workers with low RTI possess more job-specific human capital and that they assign a higher importance to non-pecuniary benefits from their job than other worker groups.

When analysing the degree of monopsony power over time for workers performing jobs with different levels of routinness, we find that the level differences between workers with low and high RTI estimated for the pooled sample are rather stable. We find no downward trend of the labour supply elasticity to the firm over time for any worker group, and therefore conclude that labour market polarisation, in terms of decreasing outside options for workers with high RTI, has not influenced the degree of monopsony power faced by routine workers to a significant degree.

We further explore the possible mechanisms behind our main findings. We distinguish between different labour market regions and therefore test whether the effect of labour market thinness on monopsony power may be heterogeneous across workers with different RTI. In line with the theoretical expectations, we find that the labour supply elasticity to the firm increases with the urbanity of the district a worker is living in. However, the importance of urbanity is of similar magnitude for workers with low and high RTI. Therefore, while labour market thinness is an important driver of monopsony power in general, workers with different RTI are not affected differently by the reduced number of job opportunities in rural areas.

Finally, collective bargaining, which varies to a large degree at the industry level in Germany, is another important determinant of monopsony power. We find that the labour supply elasticity to the firm is much lower in industries with a low coverage rate of collective bargaining compared to industries with a high coverage rate of collective bargaining. However, our main results are not driven by composition effects in terms of industries employing workers with varying levels of RTI, as the differences in the labour supply elasticities to the firm persists for workers with low and high RTI independently of collective bargaining coverage. Therefore, unions do not seem to protect specific task groups better from monopsonistic power than other task groups.

Our results have several important implications. First, the cross-sectional differences in monopsony power show that job tasks are another individual-level dimension in explaining wage gaps between worker groups; similar to earlier results in the literature, e.g. with respect to gender or nationality. Our results suggest that controlling for job tasks could provide an additional explanation for monopsony power workers face, and hence for the resulting wage gaps. Second, the finding that routine workers face less monopsonistic power than other worker groups means that these workers are closer to the perfect competition scenario in which minimum wages lead to an unambiguous decline in jobs. Therefore, our results provide a potential explanation for recent findings from the US that minimum wage increases have had more negative employment effects for workers whose jobs are more easily automatable (Lordan and Neumark, 2018). Third, our finding that monopsony power does not display a long-run trend may come as a surprise, particularly with respect to routine workers, as the job opportunities of routine workers have declined strongly in recent decades with ongoing labour market polarisation caused by technological progress. Therefore, changes in monopsony power do not seem to be a factor contributing to increased labour-market inequality in Germany in recent decades.

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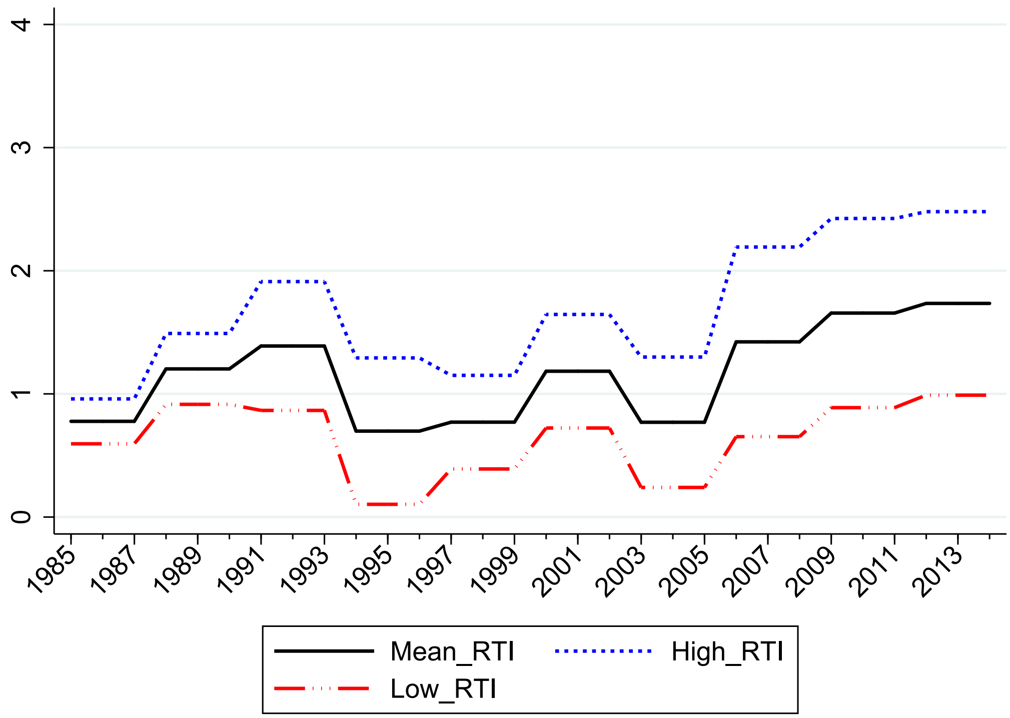
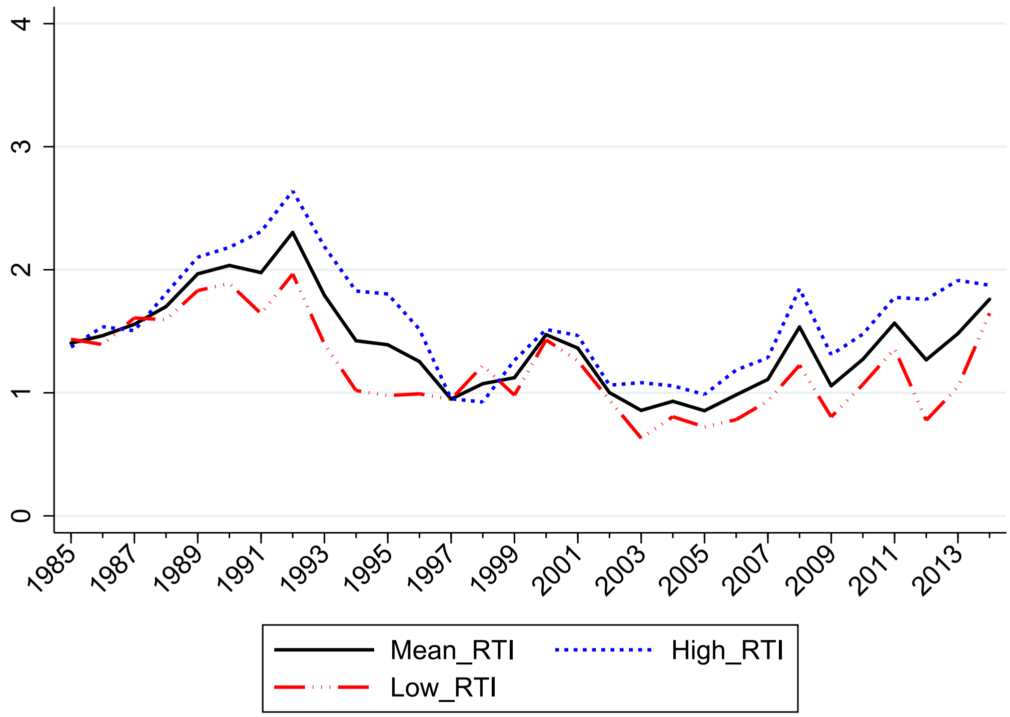
A Appendix

Figure A.1: Labour Supply Elasticities for Workers with Different RTI over 3-Year-Intervals



Notes: The estimates are derived from the same specification as Column (4) in Table 2. Further, a three-way interaction with three-year dummies is added to analyse the development over time, i.e. log wages, RTI and three-year dummies are interacted. The plotted lines correspond to the sum of the relevant coefficients for workers with mean RTI as well as workers with RTI one standard deviation below ("low RTI") and above ("high RTI") the mean.
Source: Authors' calculations based on SIAB 1985-2014, for West Germany.

Figure A.2: Yearly Labour Supply Elasticities for Workers with Different RTI. Within-worker variation.



Notes: The estimates are derived from the same specification as Column (4) in Table 2. Further, a three-way interaction with year dummies is added to analyse the development over time, i.e. log wages, RTI and year dummies are interacted. The plotted lines correspond to the sum of the relevant coefficients for workers with mean RTI as well as workers with RTI one standard deviation below ("low RTI") and above ("high RTI") the mean.
Source: Authors' calculations based on SIAB 1985-2014, for West Germany.

Table A1: Routine Task Intensity (RTI) and its Influence on the Separation Rate Elasticities and the Wage Elasticity of the Share of Recruits Hired from Employment

	Separation rate to employment	*Separation rate to non-employment*	*Hiring probability from employment*
log wage	-1.064***	-1.342***	1.821***
	(0.007)	(0.005)	(0.008)
RTI	0.784***	0.571***	0.751***
	(0.023)	(0.015)	(0.029)
log wage × RTI	-0.199***	-0.142***	-0.179***
	(0.005)	(0.003)	(0.007)
Skill group			
Upper secondary school leaving certificate or vocational training	0.261***	0.019***	0.217***
	(0.007)	(0.005)	(0.008)
University degree or university of applied sciences degree	0.561***	0.221***	-0.145***
	(0.010)	(0.008)	(0.013)
Age group			
26-35	-0.015***	-0.309***	0.554***
	(0.005)	(0.004)	(0.006)
36-45	-0.022***	-0.429***	0.575***
	(0.006)	(0.005)	(0.007)
46-55	0.244***	0.217***	0.415***
	(0.007)	(0.004)	(0.008)
Firm size			
Medium (20-250)	-0.051***	-0.069***	0.094***
	(0.004)	(0.003)	(0.005)
Large (250-999)	-0.246***	-0.169***	0.089***
	(0.006)	(0.004)	(0.007)
Very large (1000+)	-0.509***	-0.204***	-0.128***
	(0.007)	(0.005)	(0.008)
Foreign	0.023***	0.118***	-0.122***
	(0.007)	(0.005)	(0.008)
Share of high skill workers in firm	-0.229***	-0.100***	-0.307***
	(0.015)	(0.012)	(0.017)
Share of low skill workers in firm	0.087***	-0.018*	-0.135***
	(0.014)	(0.009)	(0.016)
Share of foreign workers in firm	0.492***	0.282***	-0.024
	(0.015)	(0.010)	(0.016)
Share of female workers in firm	0.277***	0.269***	0.031**
	(0.011)	(0.008)	(0.012)
Share of part-time workers in firm	-0.131***	-0.009	-0.136***
	(0.018)	(0.013)	(0.021)
Mean age of workers in firm	-0.000	0.001***	0.004***
	(0.000)	(0.000)	(0.000)
Unemployment rate	-0.007***	0.007***	-0.019***
	(0.002)	(0.002)	(0.003)
Industry dummies	yes	yes	yes
Occupation dummies	yes	yes	yes
Year dummies	yes	yes	yes
Federal state dummies	yes	yes	yes
Observations	3,644,269	7,037,147	1,339,753

Notes: Clustered standard errors at the person level in parentheses. RTI is standardized with mean zero and standard deviation one. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.
Source: SIAB and BHP, 1985-2014. Authors' calculations.