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Returning to work: regional determinants of re-employment after major redundancies

Emelie Hane-Weijman^a , Rikard H. Eriksson^b  and Martin Henning^c 

ABSTRACT

Using matched employer–employee data on roughly 429,000 workers made redundant from large plant closures or major downsizing in Sweden between 1990 and 2005, this paper analyses the role of the regional industry mix (specialization, related and unrelated variety) in the likelihood of returning to work. The results show that a high presence of same or related industries speeds up the re-employment process, while high concentrations of unrelated activities do not. The role of related activities is particularly evident in the short run and in regions with high unemployment. Consequently, the prospect of successful diversification is enhanced in regions with related industries.

KEYWORDS

labour market dynamics; redundancies; regional absorptive capacity; plant closure

JEL J6, J21, J24

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INTRODUCTION

When firms shut down or downsize, the workers made redundant need to find new employment to avoid the demise of the regional economy. Previous studies have provided considerable insights into how individual attributes such as age, education and tenure influence the likelihood of redundant workers becoming re-employed, becoming long-term displaced or even experiencing systematic wage loss (e.g., Eliason & Storrie, 2006; Fallick, 1996; Fredriksen & Westergaard-Nielsen, 2007; Huttunen, Møen, & Salvanes, 2015; Oesch & Baumann, 2015; Tomaney, Pike, & Condford, 1999). However, it is not only individual factors that are likely to influence the process of ‘returning to work’. Bluestone (1984) emphasized the importance of the region’s ability to accommodate redundancies by re-employing laid-off workers: the labour market’s absorptive capacity.¹ Recently, similar arguments have been made concerning how economic characteristics influence regional re-employment rates (Nyström, 2017).

Indeed, regional labour markets seem to be endowed with different abilities to absorb redundant workers. However, what the absorptive capacity of regional labour


markets actually consists of and how its qualitative characteristics relate to individuals’ chances of finding new employment at different points in time after the redundancy are questions that deserve more detailed study (cf., Diodato & Weterings, 2015; Eriksson, Henning, & Otto, 2016; Shuttleworth, Tyler, & McKinstry, 2005; Sunley, Martin, & Nativel, 2001). In this paper, we test the notion that important aspects of the absorptive capacity of regional labour markets can be found in the industry mix of the region. If this holds true, the extent to which individual skills and experiences match the demands of other industries present in the region should matter for individuals’ re-employment chances.

Therefore, we investigate how and when the regional industry mix – conceptualized as the presence of firms in same, related or unrelated industries in the region – influences the probability of individuals returning to work. Empirically, we do this by analysing labour market outcomes for the roughly 429,000 employees who were separated from their jobs following large plant closures or major downsizing in Sweden between 1990 and 2005. We follow the labour market status of the individuals over five years after they became redundant, and record how their


CONTACT

^a (Corresponding author)  emelie.hane-weijman@umu.se

Department of Geography and Economic History, Umeå University, Umeå, Sweden.

^b  rikard.eriksson@umu.se

Department of Geography and Economic History, Umeå University, Umeå, Sweden.

^c  martin.henning@handels.gu.se

School of Business, Economics and Law, University of Gothenburg, Gothenburg, Sweden.

re-employment probabilities correlate with the industry mix of their region.

We add to the existing knowledge by stressing the importance of the regional industry structure for re-employment. By controlling for a number of individual-level variables and regional aggregates, we demonstrate that the presence of related industries plays a significant role in shaping workers' re-employment opportunities. This is important because it reflects the role of the regional industry structure facing workers who become unemployed. By following individuals and their individual-level labour market outcomes over time, rather than relying on aggregate regional re-employment ratios, we can also show that the role of the regional industry-mix varies between those who obtain a new job quickly after becoming redundant and those who face many years of unemployment, and that the role of economic variety depends on the employment rate in the region.

The paper is structured as follows. The next section reviews the previous literature and findings on individual and regional factors influencing redundant labour's way back to employment. The third section presents the data and the empirical strategy, followed by a descriptive overview of the data and analytical results in the fourth section. The fifth section concludes.

REDUNDANCIES, INDIVIDUAL FACTORS AND THE REGIONAL ECONOMIC STRUCTURE

Over a number of decades, a vast body of literature has developed concerning the situation of workers after company closures (e.g., Fallick, 1996). Typically, a large proportion of workers who lose their job due to a plant closure leave unemployment within the first couple of years (e.g., Eliason & Storrie, 2006; Gripaios & Gripaios, 1994; Huttunen, Møen, & Salvanes, 2011; Oesch & Baumann, 2015; Tomaney et al., 1999). Nevertheless, the fact that most people subjected to major lay-offs are actually not *displaced* (i.e., become marginalized in the labour market) does not mean that job-to-job transitions come without costs. Redundant workers generally face adjustment costs in terms of unemployment and/or training or education (Ohlsson & Storrie, 2012), and they tend to end up at lower occupation levels (Bailey, Chapain, & De Reuter, 2012) with a lower standard and wage than in their previous position (e.g., Gripaios & Gripaios, 1994; Jacobson, LaLonde, & Sullivan, 1993; Tomaney et al., 1999). Also, major lay-offs still significantly increase the probability of workers leaving the labour market altogether (Huttunen et al., 2011).

On the whole, we have considerable knowledge about how individual factors affect a person's labour market outcome following job loss. Both age and tenure tend to be negatively associated with job separation due to seniority rules (e.g., Eriksson et al., 2016; Pierse & McHale, 2015), while when actually facing redundancy older workers generally comprise the most vulnerable group (Oesch & Baumann, 2015). Previous findings have also

suggested that education increases the chances of acquiring a new job (Fallick, 1996), and increases the person's flexibility, allowing more movement between jobs (Tomaney et al., 1999; Wooden, 1988). Moreover, previous studies have shown a clear gender effect in post-redundancy outcomes, where women are much more likely to end up outside the labour market (Organisation for Economic Co-operation and Development (OECD), 2013). This is usually explained by persistent gender roles in the household (Hanson & Pratt, 1991).

In contrast to the many studies on person-specific effects, strikingly little attention has been paid to the 'demand side' of the local labour market, and how this influences re-employment possibilities following redundancies. Shuttleworth et al. (2005) argued that focusing on individual attributes only is insufficient if we wish to understand how well redundant workers respond to lay-offs. Their findings suggest that more focus needs to be directed at the structure of the local economy. As argued by Sunley et al. (2001), only focusing on the supply side of the labour market is futile in the absence of sufficient local employment opportunities. For example, it is clear that training in the absence of available jobs to match the increased supply is unlikely to be successful.

Even so, the regional demand for workers and the following local matching potential have not been altogether ignored in the previous redundancy literature. However, the regional impact on re-employment likelihood is often attributed to either regional size (e.g., Puga, 2010) or regional unemployment rates (Bailey et al., 2012; Fallick, 1996). Some studies have also suggested that the qualitative characteristics of regional industry structures constitute an important aspect of the 'absorptive capacity' of regional labour markets, that is, these markets' ability to re-employ redundant workers (Bluestone, 1984; Dawley, Marshall, Pike, Pollard, & Tomaney, 2014). Marshall (1890), who famously emphasized the availability of skills as a main benefit for localized industries, also argued that a skilled worker who loses her job in economically less dense surroundings 'has no easy refuge' (IV.X.9). Following Marshall, it is easy to conclude that a strong regional concentration of economic activities in the same industry will increase the chances of finding a job after redundancy. In a more contemporary interpretation, this is expected because the mechanisms of sharing, matching and learning develop interdependencies between regional actors (Duranton & Puga, 2004). Because both matching and learning are largely mediated via the workforce, the pool of skilled labour that develops over time can be comparatively easily re-employed in localized industries. While the importance of a specialized pool of labour was initially an essential component in the modern (regional) cluster theory (Lorenzen, 2005; Porter, 1990), few scientific studies followed Marshall's original intuition, considering clusters from the point of view of job availability for redundant workers. Power and Lundmark (2004) showed, however, how clusters create a localized labour market of their own, with comparatively high labour mobility rates. On the other hand, when regional firms commonly rely on similar

human capital resources, a negative dynamic may arise in times of general industry decline. In a very narrowly specialized economy facing an industry-specific crisis, it will be more difficult for laid-off workers to find a new job (Krugman, 1993). When major redundancies occur, there is a risk of fierce competition for available same-industry jobs in the region, and strong regional specialization could then lead to a negative competition effect for the redundant workers.

In such cases, for the region to handle structural change and absorb laid-off workers, there is a need for a variety of regional industries. Empirically, there tends to be a close positive relationship between economic variety and urbanization patterns (e.g., Boschma, Eriksson, & Lindgren, 2014). While it is well established that the chances of becoming re-employed are often higher in large regions due to the availability of a wide variety of economic activities (Puga, 2010), Boschma et al. (2014) argued that the concentration of *related* industries increases the quality of regional matching. Contributions by Frenken, Van Oort, and Verburg (2007), Diodato and Weterings (2015) and Eriksson et al. (2016) have all emphasized the importance of the presence of related regional industries in hampering regional unemployment levels, or improving redundancy outcomes.

Although most employees seem to prefer to take on new work in the same industry they left (Eriksson et al., 2016), moving to related industries may be a feasible option for many. The reason for this has been theoretically discussed by Neffke and Henning (2013), who argued that the transfer of workers to skill-related industries reduces the loss of accumulated human capital (which can be at least partially used in the new industry). The empirical evidence on the connection between redundancies and labour market effects induced by related moves is, however, mixed. While both Jacobson et al. (1993) and Eriksson et al. (2016) have found less of a wage decrease for workers who attained a new job in *related* industries compared with people who moved to industries unrelated to their former industry experience, Neffke, Otto, and Hidalgo (2017) documented no such wage effects and found no positive effects of the regional presence of related industries. However, they did find that presence of related industries reduces the likelihood of regional migration after job loss.

While regional characteristics such as the industry mix may influence individuals' prospects of re-employment (Neffke et al., 2017), recent contributions have emphasized that re-employment patterns are likely to also be influenced by the strategies individuals chose after becoming redundant as a mean to adjust to economic shocks. These strategy choices are influenced by, for example, individual resources in combination with the regional socio-economic context (cf., MacKinnon, 2017). Indirect evidence concerning variations in redundancy adjustment costs among labour force groups can also be found in the redundancy literature. For example, because older workers tend to have accumulated more firm- and industry-specific human capital during the course of their careers (Bailey et al., 2012), younger workers tend to have lower transaction costs for

changing industry or migrating, or devoting time to training and education.

There are important time dimensions to the re-employment patterns of redundant workers. However, due to the heavy data demands, few studies to date have investigated these patterns systematically. Analysing the closure of an MG Rover factory in the UK, Chapain and Murie (2008) concluded that the plant closure gave rise to both a long-run quantitative *and* qualitative mismatch: long-term unemployment spells and increased turnover due to underemployment at the new job respectively. Ohlsson and Storrie (2012) showed that regional labour market policies following large-scale redundancies had two very different effects in the short and long runs. While investments aimed at increasing the basic level of education among employees had a very positive effect both on employment probabilities and on wage developments, they also caused a lock-in effect in the short run due to the time-consuming process of upgrading the workforce. Even though empirical evidence on re-employment patterns over time is only partial, these few studies suggest that re-employment outcomes must be studied over time if we are to cover more fully the major individual- and regional-level factors influencing individuals' re-employment probabilities after redundancy.

DATA AND EMPIRICAL STRATEGY

The present empirical analysis is based on longitudinal matched employer–employee micro-data from Statistics Sweden, covering the entire Swedish workforce. In contrast with most previous studies, this investigation includes all sectors: manufacturing as well as service industries. From this total dataset, and in line with Jacobson et al. (1993), we constructed a 'major redundancy sample' to identify more closely situations in which the size of the redundancy put severe pressure on the local labour market. This includes individuals from plants that experienced a job destruction of at least 100 employees between two consecutive years, and where these workers constitute at least 50% of the plant's workforce. Because our data do not include information on the decision to change workplace, the substantial changes in plant employment defining our sample are likely to be outcomes of decisions forced upon the workers, and not dominated by voluntary exits.² Consequently, our final dataset enables us to follow 428,594 workers, from 14,214 plants, who were made redundant between 1990 and 2005 (9320 firms). We follow these workers over a five-year period after becoming redundant.

Artificially constructed labour mobility resulting from within-firm organizational change may be a major confounding factor in our measures. Therefore, we excluded all observations from plants where at least 75% of all redundant employees are working in the same firm and region the year after the observed job separation. Also, workers who have been given monetary compensation for either retirement or long-term illness that amounts to a sum comparable with the subsistence level were excluded. We find it

reasonable to expect that these groups are no longer available on the labour market.

To assess the absorptive capacity of the regional labour markets, a number of indicators of the composition, or industry mix, of regional economies were calculated. We use the 72 functional labour market regions (FA regions) defined by the Swedish Agency for Economic and Regional Growth. The advantage of using these spatial units is that they are defined based on inter-municipality commuting patterns and economic coherence.

To quantify the regional industry mix that faces a redundant worker trying to find a new job, we calculate measures of shares of same (Same), related (Rel) and unrelated (Unrel) activities in the region, in relation to the industry in which the individual worked when becoming redundant (year t_0). While 'Same' is conventionally the number of people employed in the same four-digit sector in the region, the definition of related and, hence, also unrelated industries vary in the literature. The need to develop a more diverse and dynamic understanding of relatedness has been recognized in several contributions, but recent measures have been focusing on a worker-centred definition of relatedness (cf. Bishop & Gripaos, 2010; Boschma et al., 2014; Neffke & Henning, 2013; Wixe & Andersson, 2017).

In our case, however, the use of a labour-flow-based definition of industry skill relatedness (Neffke & Henning, 2013) runs the risk of circular reasoning as this paper is analysing labour flows and that is their tool of measurement. Hence, rather than focusing on industrial variety as such, we use occupations when defining the extent of inter-industry relatedness. Occupations reflect what people do in their daily work, and are therefore frequently regarded to be a direct proxy for skills and abilities (Autor, Levy, & Murnane, 2003; Wixe & Andersson, 2017). Also, Huttunen et al. (2011) discuss the possibility of skills being occupation specific, and Wixe and Andersson (2017) argue that contemporary regions tend to specialize in functions rather than industries, which means that the spatial sorting of occupations is more pronounced than that of industries.

Similar to the management literature (e.g., Tankrivedi & Venkatraman, 2005), we define human resource relatedness based on the co-occurrence of occupations across industries. To establish the 'occupation-based industry relatedness' measure, we use the strategy of Farjoun (1994). First, we calculate the pooled share of individuals in a specific occupation in each four-digit industry. For each industry, this gives a vector of the shares of each occupational category. Second, pairwise correlations between the industry occupational vectors are calculated for each possible industry combination. Third, we defined two industries as occupational-related (henceforth, 'related') if they have a statistically significant correlation of their occupation vectors of at least 0.75. After applying this procedure, we obtain 2812 links between related four-digit industries in the whole economy.³ About half are between manufacturing industries, the other half between service industries. Only about 5% are links between service and

manufacturing. The measures of unrelated variety (UV) and related variety (RV) are calculated in line with Frenken et al. (2007). UV is measured using the regional composition of two-digit sectors:

$$UV = \sum_{i=1}^n S_i \ln\left(\frac{1}{S_i}\right) \quad (1)$$

where S_i is the share of two-digit sector i employment in a region with n different two-digit sectors. RV is measured in the same way but with the five-digit variety within a two-digit sector in a region. Instead of summing the RV up to the regional level akin to Frenken et al. (2007) and Nyström (2017), they are kept sector specific (two-digit) in line with Bishop and Gripaos (2010). The reason is that the mechanisms influencing re-employment is given by the presence of related/unrelated industries in relation to the industry in question, and not the region as a whole. However, it is of course likely that the likelihood of finding a job in the same, a related or an unrelated industry is a function of not only their presence but also their growth. Therefore, absolute growth between t_0 and $t+1$ of (1) the same industry as the individual left, (2) related industries and (3) unrelated industries is included in our estimations.

Many previous studies (e.g., Fallick, 1996) have tended to proxy the economic state of the regional economy using unemployment shares. Similarly, in our case, the regional share of people of working age who are not employed (Unemployees) is calculated. Regional population size is also included in our regressions, as well as the regional ratio of small and medium-sized enterprises (SMEs), because SMEs are considered important employment contributors (e.g., OECD, 2012). To control for individual-level effects, we have included variables for age, sex, income and level of education. Finally, an additional control for whether a worker moves from the original home region (t_0) is also introduced (see Table 1 for definitions and descriptives).

RESULTS: RETURNING TO WORK

The spatiality of Swedish redundancies and absorption capacity

Given experiences of failed efforts to rescue the demising shipbuilding sector through public intervention in the 1970s and early 1980s, the Swedish state has since been reluctant to assist in rescuing specific firms or industries faced with structural problems. Instead, policies have been aimed at the redistribution of redundant workers into other jobs, industries and regions. During the period of redundancies studied here, 1990–2005, the Swedish economy experienced stable periods of growth as well as two major crises. In line with many other Western countries (e.g., Bristow, 2010), the 1990s marked the start of a shift towards more supply-driven policies supporting knowledge-intensive production (e.g., knowledge-intensive business services – KIBS). The crises, growth and transformation of the Swedish economy during

Table 1. Variable definitions and means (total sample and for each quantile of re-employment represented in Figure 1(b)).

Variable	Definition	Mean					
		All	1Q	2Q	3Q	4Q	5Q
ReEmp	Dummy = 1 if re-employed	0.93	0.84	0.90	0.92	0.94	0.95
<i>Industry mix</i>							
Same	Plant-specific concentration (%) of employees in the same industry in the functional labour market region (FA region) (log) in t_0	-5.22	-6.12	-5.34	-5.52	-5.03	-5.88
Related	Plant-specific concentration (%) of employees in related industries in the FA region (log) in t_0	-5.85	-5.83	-6.23	-7.26	-5.71	-4.93
Unrelated	Plant-specific concentration (%) of employees in unrelated industries in the FA region (log) in t_0	-0.04	-0.04	-0.04	-0.05	-0.04	-0.05
RV	Related variety. Two-digit specific variety of five-digit industries in each FA region (employees)	1.79	1.68	1.69	1.76	1.86	1.39
UV	Unrelated variety. FA regional composition of two-digit sectors (employees)	0.06	0.08	0.08	0.09	0.05	0.07
<i>Regional variables</i>							
UnEmp	Rate of adult regional population (%) that is not in the labour force in t_0	0.25	0.24	0.25	0.24	0.25	0.25
RegSize	Size of the population in the FA in t_0 (log)	13.01	11.03	11.91	11.50	13.71	11.21
SMEratio	Rate of small and medium-sized enterprise (SME) plants in region (10–249 employees) in t_0	0.18	0.19	0.19	0.18	0.18	0.19
IndDev	Employment development t_0-t_1 in the industry employed in t_0	-240.33	-34.69	-111.11	-233.93	-281.53	-194.37
RelIndDev	Employment development t_0-t_1 in related industries to industry employed in t_0	180.67	77.15	23.60	-1.55	253.49	53.02
UnrelIndDev	Employment development t_0-t_1 in unrelated industries to industry employed in t_0	2537.51	-329.93	-95.14	-492.47	3834.44	199.55
<i>Individual variables</i>							
Time	Time of re-employment after job separation	1.23	1.41	1.30	1.28	1.21	1.16
Age 16–34	Age of worker t_0 is between 16 and 34 years	25.95	23.79	25.10	25.49	26.28	26.38
Age 35–49	Age of worker t_0 is between 35 and 49 years	41.89	42.01	41.89	42.07	41.83	42.19
Age 50–65	Age of worker t_0 is between 50 and 65 years	53.55	53.71	53.51	53.43	53.53	53.69
Woman	Dummy = 1 if the worker is a woman	0.42	0.47	0.42	0.43	0.43	0.27
HiEdu	Dummy = 1 if the worker has a bachelor's degree	0.17	0.06	0.10	0.10	0.20	0.12
Income	Wage in t_0 (log)	7.45	6.89	7.21	7.35	7.51	7.63
Moved	Dummy = 1 if changed residence region from t_0	0.11	0.19	0.14	0.13	0.09	0.08

the 1990s and early 2000s also had a profound spatial bias. Many of the most expanding sectors agglomerated in the largest Swedish regions, leaving the more sparsely populated regions fewer opportunities for renewal and development (Eriksson & Hane-Weijman, 2017; Eriksson & Hansen, 2013; Henning, Lundquist, & Olander, 2016).

All in all, according to our data set, about 79% of the redundant workers found new employment the year after losing their job. This is broadly in line with other studies on redundancies in countries similar to Sweden. Yet the

figure is rather high in an international perspective (OECD, 2013). After the first year, a rather stable share of about 23% of workers not re-employed in previous years become re-employed each consecutive year. Overall, there is a distinct difference in the outcome of redundancies between the first year after job separation ($t+1$), which shows a high re-employment rate, and the period $t+2$ through to $t+5$, which displays much lower re-employment rates for those remaining workers who did not achieve re-employment in year $t+1$.

Figure 1 maps the regional redundancy and absorption capacity quantiles in Sweden. Figure 1(a) shows the rate of redundant workers (through large plant transformation) per capita in each functional region. The top quantiles are situated in the two biggest metropolitan regions, Stockholm in the east and Gothenburg in the west, while the third metropolitan region (Malmö in the south) belongs to the first quantile. Figure 1(b) shows the re-employment rates in the first year following job separation. It reveals some distinct spatial differences in the short run (the region in all maps being the region from which workers became laid-off in year t_0), from only 21% up to levels as high as 95%. Similarly substantial spatial variations have been previously found for all displacements (Nyström, 2017; Nyström & Viklund Ros, 2017). Although there are obvious spatial patterns in the re-employment rates with 'clusters' of regions with similar absorptive capacity, the differences do not seem to follow a clear urban/rural or core/periphery pattern, as also high scores are found in the more sparsely populated regions in the northern inlands and the areas between Stockholm and Gothenburg. As also displayed in Table 1, the largest regions, with a higher share of highly educated (a bachelor's degree or higher), are found in the fourth quintile on rate of re-employment (i.e., Figure 1(b)), while the regions with the highest shares of related and unrelated industries are found in quintile group 3. Thus, there are some differences in size and industry mix in different types of regions, while most other variables do not differ a great deal between quintile groups.

Indeed, the descriptive spatial variations suggest that a closer look at the regional characteristics would be of interest. Also, we know from previous studies (e.g., Eriksson, Lindgren, & Malmberg, 2008) that most Swedish workers are reluctant to change labour market. This is confirmed in

our data, as only 16% of all re-employed $t + 1$ take a job in a labour market outside of their home region. As a vast majority of redundant workers stayed in the same labour market region for the whole period in which we followed them, it is reasonable to assume that the absorptive capacity of the regional labour market in the first year is crucial. Indeed, the spatial pattern of absorptive capacity in the short run (Figure 1(b)) is more or less the reversed pattern of Figure 1(c), which shows the rate of workers who end up not becoming re-employed for as long as we follow them in our study.

As a first empirical experiment, we split individuals into groups, separated by the quantiles depending on the industry mix, i.e., the degree of presence of same, related or unrelated industries in the region. In Figure 2, this is represented by the x -axis, with observations in the group with the lowest concentration of same/related/unrelated industries to the left, and the highest to the right. For each group, the share of individuals who become re-employed in $t + 1$ is recorded. The regional concentration of workers in the same industry gives some mixed indications, suggesting that these particular results vary between different groups in our sample. Concerning the presence of unrelated industries, the re-employment rates do drop substantially (by more than 5 percentage points) when moving from low to high presence. By far the strongest descriptive indication of the importance of the industry mix is given by the presence of related industries in the region. Moving from the group including individuals with the lowest presence to the second highest group increases re-employment rates by almost 9 percentage points. Even though the rates drop slightly for the highest group, they are still far above the lower groups. The descriptive association between related presence and

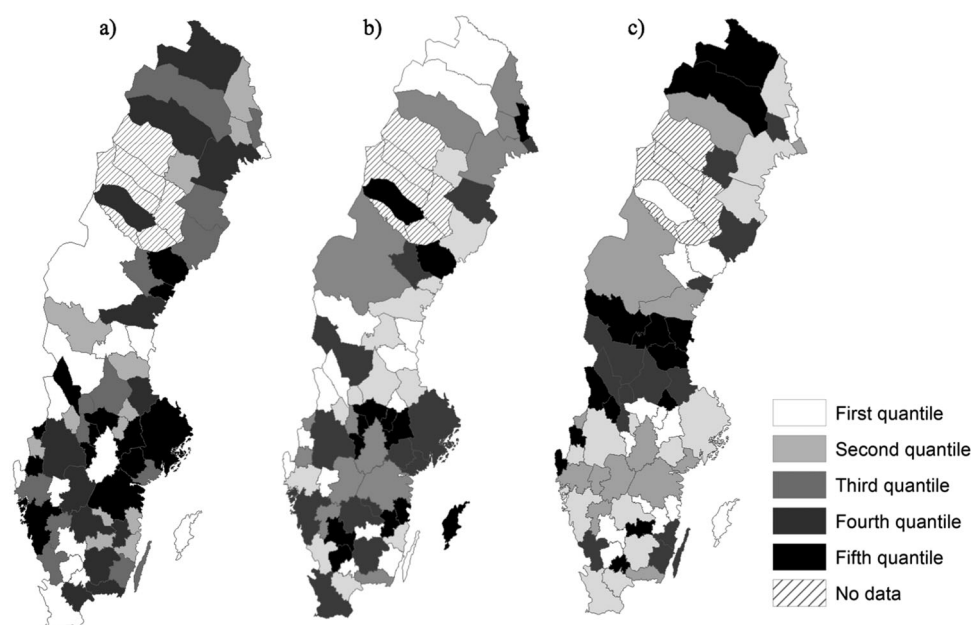


Figure 1. Regional redundancy and absorption capacity quantiles: (a) redundant workers per capita; (b) rate of all redundant workers who become re-employed in $t + 1$; and (c) who never become re-employed. The darkest shaded areas indicate the top quantile, while the lightest areas indicate the lowest quantile.

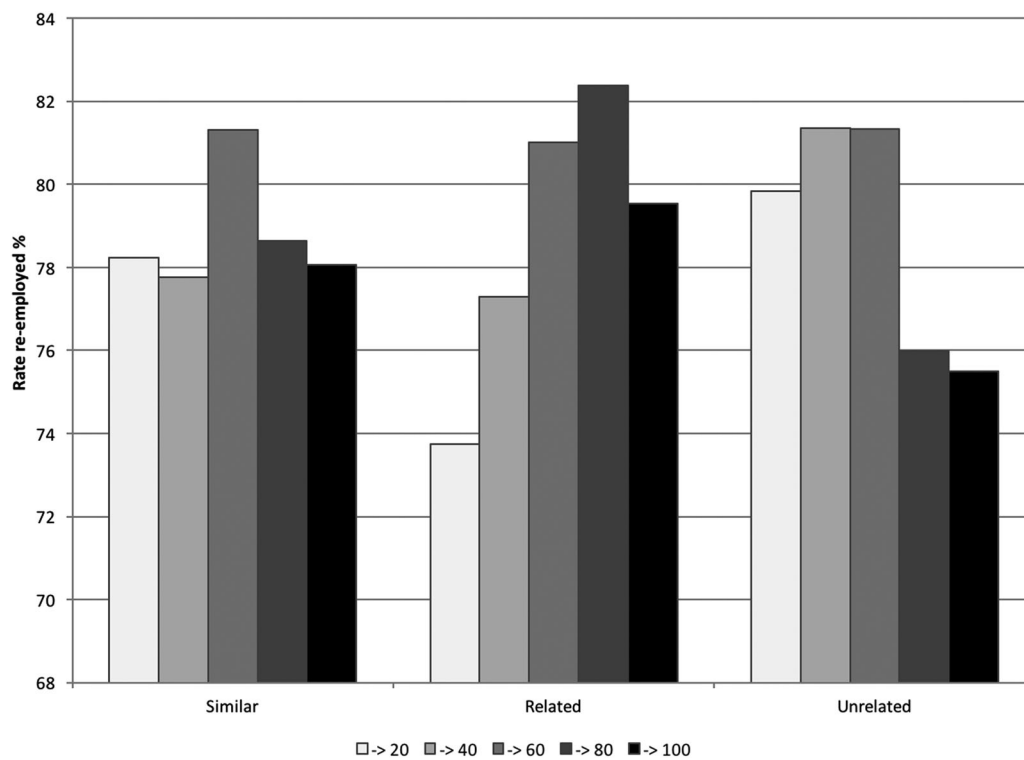


Figure 2. Rate re-employed by quintile groups of similar, related and unrelated industry concentrations in regions.

re-employment in Figure 2 suggests that the regional industry mix is an important component of the absorptive capacity of regional labour markets.

Effects of regional structure on re-employment possibilities

Turning to the analytical evidence based on methods that enable us to control for individual-level effects in a more sophisticated way, Table 2 shows the results from nine different logit models on the probability of becoming re-employed (binary = 1 if re-employed, and 0 otherwise), one to five years after redundancy. Because all observations are gathered on an annual basis, data are recorded in discrete time. Hence, performing a standard continuous-time competing-risk model could imply problems estimating the time to re-employment. Instead, we run a discrete-time survival analysis using a logistic regression where the time-to-event becomes the probability of exiting unemployment into a new job. In this way, we can take advantage of our panel-data structure, including all individuals for each year up until they exit through becoming re-employed. The model in simple form:

$$\text{logit}[h_j(t)] = \log \left[\frac{h_j(t)}{1 - h_j(t)} \right] = \alpha(t) + \beta x_j + \beta x_j(t) \quad (2)$$

where the probability of re-employment ($Y = 1$) in a given year (t) is given by the fact that the worker was not re-employed the previous year. $\alpha(t)$ refers to constraints given by five different year dummies included in the regression to allow different hazard rates for each year. βx_j refers to a vector of time-invariant variables; while $\beta x_j(t)$

is a vector of independent variables that are time variant. All models are estimated with industry- (four-digit level), regional- (functional regions) and year-specific fixed effects to moderate the influence of unobserved heterogeneity. For example, workers might sort in space based on unobserved regional or industry characteristics such as amenities or industry-related life-cycles (cf. Neffke et al., 2017). All standard errors are clustered at the individual level because we have repeated observations on individuals (it is reasonable to expect correlation within individuals over time). As the industry-mix variables exhibit some correlation (especially related and unrelated activities), we introduce them stepwise in the models.

In line with the standard expectation that regional unemployment is an indicator of a labour supply that is already too high compared with the demand (Fallick, 1996), Table 2 shows that a high rate of people of working age outside employment in the region (Unemployees) decreases the probability of re-employment. However, our results also indicate significant influences of the regional industry mix. A strong regional presence of activities in the same industry in which the worker previously worked does indeed increase the probability of becoming re-employed in the first year (model 1). However, a similar outcome is found from a high regional concentration of *related* activities based on occupational similarities (model 2). The marginal effects (not reported) indicate similar effects of both variables (0.007).⁴ However, as shown in model 3, the likelihood of becoming re-employed significantly decreases with an increasing share of *unrelated* industries in the region (marginal effect = -0.529).⁵ If we assume a 'baseline' probability at the mean of $Y = 1$ (0.93; Table 1), this implies that the

Table 2. Discrete-time survival analysis using a logistic regression for the probability of becoming re-employed.

	Model 1 Same Occupation	Model 2 Rel Occupation	Model 3 Unrel Occupation	Model 4 Rel Unrel Occupation	Model 5 RV UV Industry	Model 6 Rel Unrel#Unemp Occupation	Model 7 RV UV#Unemp Industry	Model 8 Rel Unrel#Time Occupation	Model 9 RV UV#Time Industry
Same	0.0307*** (0.00301)								
Related/RV		0.0293*** (0.00433)		0.0184*** (0.00469)	0.0281 (0.0249)	0.00198 (0.00894)	0.0571 (0.0427)	0.0174*** (0.00486)	-0.165*** (0.0252)
Unrelated/UV			-2.258*** (0.273)	-1.835*** (0.296)	-3.010*** (1.144)	1.764*** (0.630)	-3.156** (1.339)	-3.723*** (0.311)	-2.456** (1.148)
Unemp	-5.207*** (0.694)	-5.216*** (0.696)	-4.809*** (0.696)	-4.878*** (0.697)	-5.324*** (0.697)	-5.075*** (0.755)	-5.157*** (0.830)	-4.873*** (0.698)	-5.104*** (0.694)
Rel/RV#Unemp						0.0702** (0.0313)	-0.118 (0.141)		
Unrel/UV#Unemp						-15.36*** (2.319)	0.727 (4.378)		
Time	-0.0872*** (0.0199)	-0.0871*** (0.0199)	-0.0871*** (0.0199)	-0.0870*** (0.0199)	-0.0873*** (0.0199)	-0.0865*** (0.0199)	-0.0873*** (0.0199)	-0.0372* (0.0213)	-0.289*** (0.0227)
Rel/RV#Time								0.000767 (0.000826)	0.111*** (0.00406)
Unrel/UV#Time								1.013*** (0.0714)	-0.355*** (0.0928)
IndDev [†]	-0.0557* (0.0303)	-0.0590* (0.0303)	-0.0579* (0.0301)	-0.0617** (0.0302)	-0.0540* (0.0303)	-0.0831*** (0.0306)	-0.0530* (0.0307)	-0.0635** (0.0301)	-0.0611** (0.0303)
RelIndDev [†]	0.269*** (0.0357)	0.268*** (0.0357)	0.288*** (0.0358)	0.287*** (0.0358)	0.261*** (0.0358)	0.288*** (0.0359)	0.262*** (0.0358)	0.284*** (0.0356)	0.249*** (0.0358)
UnrelIndDev [†]	-0.00891** (0.00386)	-0.00897** (0.00387)	-0.0103*** (0.00387)	-0.0104*** (0.00387)	-0.00770** (0.00388)	-0.00851** (0.00388)	-0.00710* (0.00428)	-0.00989** (0.00388)	-0.00693* (0.00387)
RegSize	-0.251 (0.201)	-0.185 (0.201)	-0.104 (0.202)	-0.106 (0.202)	-0.181 (0.202)	-0.0844 (0.202)	-0.176 (0.203)	-0.134 (0.202)	-0.249 (0.201)
SMEratio	5.155*** (0.782)	5.217*** (0.783)	5.464*** (0.783)	5.501*** (0.783)	3.818*** (0.910)	5.542*** (0.784)	3.830*** (0.912)	5.591*** (0.784)	3.577*** (0.907)

(Continued)

Table 2. Continued.

	Model 1 Same Occupation	Model 2 Rel Occupation	Model 3 Unrel Occupation	Model 4 Rel Unrel Occupation	Model 5 RV UV Industry	Model 6 Rel Unrel#Unemp Occupation	Model 7 RV UV#Unemp Industry	Model 8 Rel Unrel#Time Occupation	Model 9 RV UV#Time Industry
<i>Age (reference 16–34 years)</i>									
Age 35–49	0.654*** (0.00987)	0.652*** (0.00987)	0.652*** (0.00987)	0.652*** (0.00987)	0.652*** (0.00987)	0.651*** (0.00987)	0.652*** (0.00987)	0.652*** (0.00988)	0.651*** (0.00987)
Age 50–65	0.647*** (0.0145)	0.645*** (0.0145)	0.646*** (0.0145)	0.646*** (0.0145)	0.645*** (0.0145)	0.645*** (0.0145)	0.645*** (0.0145)	0.645*** (0.0145)	0.648*** (0.0145)
Woman	–0.377*** (0.00881)	–0.376*** (0.00882)	–0.377*** (0.00881)	–0.376*** (0.00881)	–0.377*** (0.00881)	–0.376*** (0.00882)	–0.377*** (0.00881)	–0.379*** (0.00883)	–0.373*** (0.00881)
HiEdu	0.873*** (0.0123)	0.874*** (0.0123)	0.873*** (0.0123)	0.873*** (0.0123)	0.873*** (0.0123)	0.871*** (0.0123)	0.873*** (0.0123)	0.871*** (0.0123)	0.872*** (0.0123)
Income	0.848*** (0.00484)	0.847*** (0.00484)	0.848*** (0.00484)	0.848*** (0.00484)	0.847*** (0.00484)	0.847*** (0.00484)	0.847*** (0.00484)	0.848*** (0.00485)	0.846*** (0.00484)
Moved	–0.237*** (0.0171)	–0.237*** (0.0172)	–0.238*** (0.0171)	–0.237*** (0.0171)	–0.237*** (0.0171)	–0.237*** (0.0171)	–0.237*** (0.0171)	–0.238*** (0.0172)	–0.234*** (0.0172)
Constant	–2.551 (2.903)	–3.516 (2.904)	–4.947* (2.910)	–4.802* (2.913)	–3.372 (2.903)	–5.112* (2.913)	–3.480 (2.934)	–4.521 (2.915)	–1.972 (2.893)
<i>n</i>	428,594	428,594	428,594	428,594	428,594	428,594	428,594	428,594	428,594
<i>N</i>	678,434	678,434	678,434	678,434	678,434	678,434	678,434	678,434	678,434
Pseudo- <i>R</i> ²	0.408	0.408	0.408	0.408	0.408	0.408	0.408	0.409	0.409

Note: Figures shown in thousands are denoted with a dagger (†). Significant at 10% (*), 5% (**) and 1% (***) level. Standard errors (SE) are shown in parentheses. All models include a full set of region, industry and time dummies.

expected probability of both similar and related industries only marginally influences the chance of re-employment (0.94 respectively). However, if the log of UV increases by 1, then the expected probability drops to 0.40, which is a decrease of almost 50 percentage points.⁶ When estimating related and unrelated concentrations jointly in model 4 (and hence comparing with the role of same industry concentration), these estimations remain stable and related activities increase the likelihood of re-employment compared with same industries (although with a slightly lower marginal effect of 0.005).

Our findings confirm the notion that the qualities of the regional industry mix significantly influence the probability of re-employment (Diodato & Weterings, 2015; Eriksson et al., 2016; Neffke et al., 2017; Nyström, 2017). However, how related industries are defined matters a great deal. When comparing the occupation-based proxies of the industry mix with the traditional industry-based classification of related and unrelated industries adopted from Frenken et al. (2007), we find in model 5 that RV is not significant, and that UV significantly decreases the probability of becoming re-employed (even to a greater extent than occupation-based unrelated industries, as the marginal effect for industry-based unrelatedness is -0.705 compared with the occupation-based counterpart where the marginal effect is -0.529).

Before turning to an expanded set of models, we note that the control variables are, by and large, in line with expectations. Growth in related industries tends to be positively associated with re-employment probabilities, whereas growth in the same or unrelated industries is not. SMEs tend to be important job creators that can absorb some of the shock, and being located in a large region seems to prolong the spell of unemployment. This latter finding might run counter to ideas concerning the benefits of thick labour markets (Duranton & Puga, 2004). However, previous studies have shown that larger regions are, on average, more expensive to live in. This implies that the reservation wage might be higher, meaning a longer duration of job search (Jones, 1988). A greater supply of more well-paid jobs in larger regions also makes it possible to extend the unemployment period in search of a 'better' job (Wilkin, 2012). The search cost can thus be greater, because the utility gain associated with a new job is higher in these regions.

Moreover, the individual controllers are consistent across the models and show the expected signs, with the exception of *age*. In contrast to previous studies, the results suggest that more senior workers are more likely to be re-employed. However, this result has a clear time dimension. To control for the dynamics of this effect, we introduce an interaction term between time and age, which shows that after year $t + 1$ people of higher age will have a much harder time returning to work. This corresponds with previous findings indicating tendencies towards a time-sensitive selection process (e.g., Oesch & Baumann, 2015) where the advantage of age is played out after year $t + 1$.

Given the aggregate findings of Nyström (2017), we expect that the influence of the regional industry mix

may have different outcomes depending on the state of the local economy. When interactions between the industry-mix variables and regional unemployment are introduced (t_0) in model 6, the rate of unemployment in the region still has a significantly negative influence on re-employment, while the significance of related activities disappears. However, the previously positive influence of related industries is picked up in the interaction effects. This suggests that a regional industry portfolio of industries with related occupations is especially important for the absorptive capacity of regions facing high unemployment. While a high share of unrelated activities has become significantly positive, the interaction term suggests that this positive impact is not present in regions with high unemployment. In relation to the industry-based indicators of Frenken et al. (2007) in model 7, unemployment does not seem to moderate this group of workers' prospects of returning to work. This is in line with more recent contributions arguing for the importance of related industries in facilitating qualitative matching (Boschma et al., 2014). Conversely, when assessing industry variety in relation to the specific plant subject to closure or major downsizing, UV is mainly a positive feature in already buoyant regional economies where the demand for a variety of skills is high.

When introducing an interaction between the industry mix and time to re-employment, some notable time-specific effects appear. While occupation relatedness (model 8) remains significantly positive, the interaction between time to re-employment and relatedness shows that this positive relationship diminishes over time. The longer the time to re-employment for the individual, the greater the need for a more diverse (unrelated activities) labour market composition. This corresponds to the argument made by MacKinnon (2017), which is that, when regarding how workers adapt to changes in the regional economy, they are more likely to be pushed further away from their core skills the longer the time to re-employment. Still, as shown in model 9, when the industry variety is analysed, the presence of related industries increases the chances of re-employment for the group of workers not instantly re-employed.

Finally, neither subsequent variance inflation factor (VIF) tests nor pairwise correlations showed signs of multicollinearity that might influence the results.⁷ To check further for the robustness of these findings, a number of alternative model specifications were estimated. The results of the robustness checks did not lead to any reinterpretations of our main results, and are accounted for in Appendix A in the supplemental data online.

CONCLUSIONS

This paper investigated how regional economic structures influence individuals' post-redundancy re-employment possibilities. Indeed, recent research efforts have emphasized that the prospects of returning to work depend not only on individual attributes, such as education or tenure, but also on regional factors (e.g., Bluestone, 1984; Dawley

et al., 2014; Eriksson et al., 2016; Neffke et al., 2017; Nyström, 2017; Shuttleworth et al., 2005). In theoretical terms, these factors could be considered to form the 'absorptive capacity' of regional labour markets. In line with this emerging literature, but trying to operationalize what absorptive capacity actually consists of, we find that an individual's labour market status after becoming redundant is not solely determined by individual characteristics. The surrounding industry structure – especially the presence and growth of same and related industries – also matters a great deal. In theoretical terms, the absorptive capacity of the regional labour market is thus crucial in forming individuals' post-redundancy experience.

In contrast to previous studies in the field (e.g., Frenken et al., 2007; Nyström, 2017), however, we found weak support for the notion that a highly diverse regional portfolio of industries is instantly beneficial, irrespective of whether it is defined in terms of occupational relatedness or industry codes. However, the longer the time to re-employment, the more likely that workers will be pushed further away from their core skills when trying to adapt to their new labour market situation (cf., MacKinnon, 2017), which increase the likelihood of beginning to work with unrelated activities. Consequently, when conceptualizing regional absorptive capacity by means of the industry mix, it is essential to consider the skill demand in the plant-specific regional context.

These general results could be further qualified in the context of regional economies. Interestingly, in a recent study on Swedish regions, Nyström (2017) found that variety (both related and unrelated) is primarily important for regional re-employment rates in regions with moderate resilience (i.e., not the highest proportions of regional re-employment rates). Our findings suggest that while having unrelated industries in terms of skill content does not generally positively influence re-employment, it does so in regions where unemployment rates are low. Conversely, the influence of related industries on the individual's chances of getting employed is particularly great in high unemployment regions under circumstances when job competition is relatively high. Thus, the type of variety that may aid workers in their attempts to return to employment depends on the economic situation in the region. Related industries are more beneficial in less buoyant regions, where the skill demands tend to be more specialized (cf. Wixe & Andersson, 2017), while UV is beneficial in relatively more buoyant regions where workers may more easily find a variety of employment opportunities.

Although the potential influence of spatial sorting of skills has been indirectly assessed in this paper by focusing on occupation-based relatedness rather than industry-specific relatedness, we have not considered in detail the extent to which increasing sorting of skills, driven by the deepened spatial division of labour, influences the chances of re-employment for different groups of workers. For example, as recently argued by Wixe and Andersson (2017), on the one hand, occupations seems to be a better proxy of what people do, but, on the other hand, they tend to be more subject to spatial sorting due

to the functional specialization of regions. While the vulnerability of manual workers in more rural regions may be high, it may actually be easier for them to find new employment locally than someone with an occupation requiring post-secondary education. Similarly, it may be more difficult for manual-skills employees to adapt if being located in one of the metro-regions as the demand for such skills is not as high in these service-specialized regions. Future studies should therefore pay more attention to the role of the industry mix for different groups in the workforce across regional settings. Probing more deeply into the issues of individual industrial mobility and how that is shaped by the surrounding socio-economic context could be instrumental in increasing our understanding of why major redundancies do not need to be disastrous for regional development, but may instead lead to a process of creative destruction.

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SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at <http://dx.doi.org/10.1080/00343404.2017.1395006>.

NOTES

1. This interpretation of absorptive capacity should not be conflated with the concept as used in the innovation literature for a firm's ability to find, assimilate and apply new knowledge in the organization (cf., Cohen & Levinthal, 1990).
2. The 'major redundancy' threshold has an impact on the regional data composition. With a minimum of 100 job separations, a large part of the workers are located in the bigger regions, where about 40% of the observations are located in Stockholm (compared with 25% of total employment).

3. We also used three-digit industries when defining same, related and unrelated industries to check for the potential impact of granularity. While the estimates for concentrations of same industries remained stable (and somewhat stronger), the role of related industries became weaker. Hence, using the three-digit level would imply categories that are too broad to separate between same and related industries effectively.
4. A difference of 1 in the respective log value is associated with an increase of 0.007 in the probability of becoming re-employed.
5. The probability of re-employment decreases by 0.529 if the variable increases by 1.
6. Because these are log values, an increase of 1 implies a 172% increase in x (as it multiplies by $e = 2.718$). Thus, increasing the share of related industries from 10% to 27% in a region increases the probability of re-employment by almost 1%, while increasing the share of unrelated industries in a region from 10% to 27% lowers the probability of re-employment by almost 50%.
7. No individual variable exceeded 1.7 in the VIF test and most variables scored around 1 (a value of 2 is a common threshold). The 1's that did score highly also displayed relatively high significant correlations. These were the unemployment rate and growth of unrelated industries (Unemp and UnrelIndDev = 0.43), the concentration of related and unrelated industries (Rel and Unrel = -0.50), regional size and unrelated variety (RegSize-UV = 0.58), as well as time to re-employment and income (Time and Inc = -0.47). However, removing any of the correlated variables influenced neither the sign nor the significance of any variable.

ORCID

Emelie Hane-Weijman  <http://orcid.org/0000-0002-8644-4766>

Rikard H. Eriksson  <http://orcid.org/0000-0003-3570-7690>

Martin Henning  <http://orcid.org/0000-0002-8081-5095>

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