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ORIGINAL PAPER

The regional and sectoral mobility of high-tech workers: insights from Finland

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Abstract In this paper we employ data on 156,000 workers working within the Finnish high-tech industries in order to identify the extent to which labour mobility between sectors and regions is influenced by the characteristics of the locality in which the worker works. With these data we are able to estimate different types of binary, multinomial and ordered logit models to capture different types of inter- or intra-sector or region employment mobility. As we will see the different categories of employment mobility are influenced by different factors such that we cannot simply talk about 'labour mobility', but rather need to be specific regarding each particular form of employment mobility. Our results show that urbanisation and industrial diversity are not just associated with greater intra-regional mobility, as is emphasised by the agglomeration literature, but also greater inter-regional mobility.

JEL Classification J61 · R1 · R23

1 Introduction

Over the past two-to-three decades, an enormous body of research has emerged in which processes of agglomeration and clustering have been examined from a range of different perspectives. At the same time there are also many papers examining different aspects of intra-regional labour adjustment processes as well as inter-regional

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mobility. Yet, although the possibilities for better matching and adjusting associated with local labour pool are often emphasised as one of the most important reasons for the clustering and agglomeration of firms, there actually exist very few empirical studies where labour mobility within and between sectors and localities has been clearly linked to the spatial distribution of activities. In particular, the evidence on the extent to which the agglomeration of firms increases labour mobility within the specific region or between regions, is actually surprisingly scarce (Di Addario 2011; Eriksson et al. 2008; Fallick et al. 2006).

A variety of evidence suggests that high-tech sectors and clusters tend to exhibit high rates of local labour turnover and mobility (Audretch and Feldman 1996; Audretsch and Stephan 1996; Almeida and Kogut 1999; Angel 1991; Arita and McCann 2000; Carnoy et al. 1997; Fallick et al. 2006; Hansen and Niedomysl 2009; Lawton-Smith and Waters 2005; Mukkala 2008; McCann and Simonen 2005; Simonen and McCann 2008, 2010; Rogers and Larsen 1984; Saxenian 1994). However, none of these papers specifically and explicitly model the nature of this mobility as a function of industry and regional characteristics. As such, we actually currently know very little about how the mobility of high-tech workers between firms, between sub-sectors, and between places is related to the particular geography and structure of these sectors. What we do know is that inter-firm, intra-sector, inter-sector, intra-regional, or inter-regional movements, all represent different possible types of labour matching and labour adjustment mechanisms and also, therefore, different types of potential knowledge-transmission mechanisms. However, which ones are dominant in which contexts is as yet unknown. As such, the inter-relationship between labour mobility, and employer and employee matching processes is unclear.

The aim of our study is therefore to provide some new insights and information about the links between the clustering and agglomeration of firms and these different forms of labour mobility in the case of the Finnish high-tech sectors using a detailed dataset covering some 156,000 individual workers.[1] More specifically, we will look both at the regional features as well as the sectoral and economic factors underpinning different labour mobility patterns within the Finnish high-tech sector. In order to do this we employ dichotomous, multinomial and ordered logit models to estimate the influences of different industrial and regional features on these different types of high-tech human capital mobility. Our basic result is that the structure of the high-tech sectors as well as a range of regional economic features, all influence the mobility of high-tech workers. We find that clustering and agglomeration is associated with greater levels of inter-industry labour mobility, as implied by much of the current literature. However, their roles vary significantly for different types of mobility, according to whether we look at within-region mobility, across-region mobility, as well as within-industry and across-industry mobility. As such, we cannot simply talk about agglomeration and labour

[1] In Finland high-tech firms and their success in international markets has been an engine of economic growth over the past two decades. The strong growth of information and communication technology cluster in the 1990s (led by Nokia Corporation) made Finland internationally known as a small technology-intensive economy where economic growth is mainly based on technology know-how. The strong high-tech sector had an extremely important role especially in early 1990s when the Finnish economy was recovering from deep recession. For instance in 2008, the share of high-tech sector was about 6 % (in 1989 3.6 %) of the total labour force and almost 18 % of the total export (in 1991, 6 %).

mobility. It is a much more complex, nuanced and interesting picture than this simple portrayal suggests.

The rest of the paper is organised as follows. In the next section we provide a brief review to the current literature by focusing on the question of how the agglomeration and other regional features affect labour mobility. In Sect. 3 we discuss the data at our disposal and the variables we employ. In Sect. 4 we examine the issues empirically using different set of logit, ordered logit and multinomial logit models. Section 5 provides a brief discussion and some conclusions.

2 Literature review

In numerous economic geography and regional science papers one of the key advantages afforded to clustering and agglomeration is the presence of a skilled local labour pool, which is argued to facilitate the matching of workers and firms and thereby reduces the search costs of both (Duranton and Puga 2004). Many have assumed that such an effect will not only better facilitate labour mobility between local firms (Di Addario 2011; Kim 1987; Scott 1988; Carnoy et al. 1997; Scott and Storper 1990) but will also help to bolster resilience to shocks and provides another reason for workers to stay local. Some studies have shown that staff turnover is considerably higher in larger urban areas (Power and Lundmark 2004; Eriksson et al. 2008), and particularly in high-tech sectors. However, as yet there is no clear evidence as to whether job changes are systematically higher in thicker local labour markets than in other markets (Bleakley and Lin 2007; Lawton-Smith and Waters 2005; Rosenthal and Strange 2004). Allied to this, the relationship between workers changing jobs locally and workers entering jobs in other localities is again largely unclear. In other words, it is unclear exactly how the characteristics of the local economy influence the likelihood of a worker entering another job in the local vicinity versus entering another job in another locality.

It is of course possible to speculate on the nature of some of these relationships. Arguments regarding urbanisation and population density suggest that they facilitate the diffusion of information on job opportunities, and therefore this variable would be expected to be associated with greater local employment switching (Di Addario 2011; Glaeser and Maré 2001). Concentration and agglomeration will also be associated with higher wages (De La Roca and Puga 2014), and from migration models we might expect that the higher is the wage in a locality, the less likely workers will be to seek employment opportunities elsewhere. Meanwhile, competition effects mean that firms' propensity to make more attractive offers may be also higher in high wage and more densely populated regions, thereby increasing the importance of knowledge spillovers and a greater search intensity in order to secure the best matches, all of which point to increased local mobility and lower inter-regional mobility (Di Addario 2011). Similarly, from incubator and nursery city arguments (Duranton and Puga 2001), we might expect that the greater the number of local establishments, or the more evenly distributed are these establishments across different sectors, the more likely will be local employment switching and less movements to other regions. However, this local employment switching may also depend on the extent to which the establishments are technologically related (Neffke et al. 2011), and if firms in other regions have a greater technological congruence with the employee's current firm, then inter-regional migration will be more likely. Similarly, the number of service sector firms in a region may also influence employment and location changes in that service industries contribute to local linkages, thereby enhancing agglomeration effects (Fingleton 2003), while also help to absorb employment (Jorgensen and Timmer 2011), thereby fostering labour market resilience to technological shocks. Each of these potential mechanisms would be expected to be influenced by the overall general economic conditions of the region. However, at this stage the likely impacts of each of these individual influences can only be speculated on, in that there is as yet no specific evidence of exactly how each of these play out in reality. Indeed, the intention of this paper is to throw some light on these issues.

3 Data and variables

Our regional labour mobility data come from the Finnish Longitudinal Employer–Employee Database (FLEED) maintained by Statistics Finland. All labour mobility variables are based on the data which tell us where individual employees have been working at the establishment level in years 2005 and 2006. The data cover all of the workers employed in high-tech industries in Finland both in 2005 and 2006, which in total accounts for some 156,000 employees.[2] The labour mobility of these high-tech workers is classified into five categories, whereby individual workers:

- Category 1: Remain in the same high-tech firm within the same industry and region
- Category 2: Change the firm within the region and stay within the same high-tech industry
- Category 3: Change the region but stay within the same high-tech industry
- Category 4: Change the high-tech industry within the same region
- Category 5: Change the high-tech industry and the region

For consistency in categories 3–5, we only use outflow numbers of employees across industries and regions rather than inflow numbers. Table 1 shows both the percentage shares of the different categories of high-tech labour and the total labour across regions and industries in Finland in 2005. When we compare these values, we see that inter-regional labour mobility seem to be more common and intra-regional labour mobility less common in the high-tech sector than in the whole economy. In particular inter-industry labour mobility within the regions is less common on the high-tech sector than it is in general in the economy in 2005. The general labour mobility values are based on the two-digit-level industrial analysis which impairs the comparison to the

[2] We exclude the workers who left the high-tech sector in 2005 and employees who entered to the high-tech sector in 2006. So we are analysing the labour mobility within the high-tech sector, both across industries and regions in 2005–2006. The data, on level of detail we have available in terms of sectoral-spatial movements, do not include individual level information. Therefore, we have adopted this particular estimation strategy. Instead of using sample of the total data, as it is the case in most of studies which use the individual data, our data covers all the high-tech workers in Finland in year pair 2005–2006.

Table 1 Percentage shares of the different categories of *high-tech labour* and *total labour* across regions and industries in 2005

	Category 1	Category 2	Category 3	Category 4	Category 5
Average					
High-tech	91.16	4.18	3.50	0.76	0.41
Total	80.90	7.27	2.04	8.85	0.86
Median					
High-tech	91.75	4.08	2.73	0.27	0.22
Total	81.72	6.99	1.98	8.71	0.92
Min					
High-tech	75.93	0	0	0	0
Total	72.42	4.19	0.97	5.84	0.39
Max					
High-tech	98.55	9.26	15.38	11.11	5.34
Total	85.14	11.61	4.86	12.61	1.60

Table 2 Percentage shares of the different categories of *high-tech labour mobility* across regions 2005 (category 1 excluded as these people do not change a job)

	Category 2	Category 3	Category 4	Category 5
Average	49.99	38.60	6.93	4.49
Median	50	33.86	2.95	2.71
Min	0	0	0	0
Max	100	100	46.15	38.89

labour mobility on the high-tech sector to some extent.[3] Table 2 shows percentage shares of the different categories of high-tech labour mobility across regions 2005.

All of the models in this paper are estimated with respect to the characteristics of the baseline origin industry and location. The regional-level and industrial-level data used for this research comes from Statistics Finland. Regional-level classification is NUTS4, as this is the regional-level which is the most frequently used unit of analysis in these types of regional growth studies in Finland. This is in part because it is the smallest administrative area where the required data is extensively available, but also because this is the geographic area (a total of 71 regional units) which best describes the commuting areas of Finland, given Finland's particular spatial population distribution.[4] Our dataset is comprised of all the Finnish high-tech establishments, as defined according to the standard industrial classification 2002 (SIC 2002) and listed

[3] The general labour mobility values are based on the data which cover 71 regions and 1,441,298 employees in a year pair 2005–2006. All the values presented in Table 1 are based on region-specific values, and for instance, they do not show the variance across regions. As a comparison to these figures approximately 3–3.5 % of the total population migrated between the sub-regions in Finland (average per year over the period of 1996–2006) (Nivalainen 2010).

[4] Because we do not have information about the regional wages of the high-tech sector in all 71 regions, the number of regions used in estimations is 64.

Table 3 High technology industries (SIC 2002)

Industry	SIC	%
High-tech industries and distribution of employment according to the industries in Finland 2005		
Manufacture of pharmaceuticals, medicinal chemicals and botanical products	244	3
Manufacture of office machines and computers	30	0.3
Manufacture radio, television, communications equipment and apparatus	32	24
Manufacture of medical, precision and optical instruments	33	8
Manufacture of aircraft and spacecraft	353	2
Telecommunications	642	12
Computers and related activities	72	26
Research and development	73	2
Architectural and engineering activities and related technical consultancy	742, 743	23

in Table 3.[5] Table 3 shows also the industrial distribution of high-tech employment in Finland 2005.

We shall estimate binomial logit as well as ordered and multinomial logit models in order to test the relationship between the different types of high-tech labour mobility and the importance of various regional variables related to the region of origin. In order to begin this we first reclassify the five mobility categories into three binary data sets as follows.

In the first case (Model A) the binary-dependent variable is defined as being equal to 0 if person remains in the same high-tech firm in the same region and value of 1 if the person exhibits any of the above mobility categories 2–5.

In the second case (Model B) the binary-dependent variable is defined as being equal to 0 if person remains in the same region (categories 2 and 4), and equal to 1 if person has changed the region (categories 3 and 5). In both cases the person may or may not have changed the high-tech industry. The estimations exclude workers who remain in a same high-tech firm in a region (i.e. category 1).

In the third case (Model C), the third binary-dependent variable is defined as being equal to 0 if person remains in the same high-tech industry (categories 2 and 3), and equal to 1, if person has changed the high-tech industry (categories 4 and 5). In both cases, a person may or may not have changed the region. Also these estimations exclude workers who remain in a same high-tech firm in a region. The dependent variables we therefore employ reflect the different categories of mobility for which we have data. In ordered and multinomial logit models (Models D and E), the categories of labour mobility are defined as shown on p. 4.

In order to model these different types of high-tech worker mobility, we employ various independent explanatory variables some of which are specific to the regional high-tech sector and some of which reflect general state of the regional economy.

[5] More information about the definition of high-tech sectors. See Eurostat Pocketbooks (2011): science, technology and innovation in Europe.

The large literature on labour mobility suggests that each of these variables ought to influence worker mobility patterns.

In terms of those variables relating specifically to the high-tech sectors, our first independent explanatory variable is the *Location quotient of the high-tech sector*, which reflects the region's relative specialisation in high-tech activities in comparison to the national average. From standard agglomeration arguments, we might expect that the greater is the high technology location quotient value of the region, the more likely high-tech workers will remain in the region. This is because the number of employment opportunities in the local area will be relatively higher in the local region than in other areas, also bolstered by the greater likelihood of localisation economies operating locally.

Our second variable is the *Regional wage in the high-tech sector*, and this is calculated as the ratio of the median local high-tech wage to the national median high-tech wage.[6] According to the arguments proposed by the disequilibrium model of migration (Muth 1971; Greenwood 1975, 1985; Greenwood and Hunt 1984), we might expect that the higher is the wage level in a particular region, the less likely workers will be to seek high-tech employment opportunities elsewhere. On the other hand, we may also assume that in high wage regions firms' propensity to make more attractive offers can increase search intensity and thereby labour mobility also within the region (e.g. Di Addario 2011).

Our third variable specific to the high-tech sectors captures the *Diversity of the high-tech sector*, and for this we use the Shannon index. The Shannon index is an entropy measure developed originally in information science which captures two features of diversity, namely richness and evenness. For this exercise the index has been calculated using the number of establishments in each of the nine different high-tech industry sub-sectors and is calculated as follows:

$$\mathrm{SI}_i = -\sum_{j=1}^{9} s_{ij} \ln s_{ij},$$

where s_{ij} is the share of industry j of the total high technology sector in region i. The larger is the number of industries and the more evenly distributed are the high-tech establishments across these industries, the higher is the value of this measure in a particular region.[7]

[6] Using the median wage overcomes the problem that some dominant regions may skew the average wage significantly, although we find that in the case of Finnish high-tech sectors the average value is very close to the median value. We use nominal values because of the lack of real values.

[7] The difference between commonly used Herfindahl–Hirschmann index (HHI) and Shannon index is that the HHI assigns higher weights to the largest branches than does the Shannon index. Therefore, the value of HHI is largely driven by the share of the dominant branch, whereas the value of the Shannon index depends more strongly on shares of several industries. Therefore, it reflects more accurately the variety of the high technology sector in terms of how many industries, including even small ones, are present in a region (Aiginger and Davies 2004; Simonen et al. 2014). The maximum value of the Shannon index is $\ln(m)$. In this case all high-tech branches are present in a particular region and employment is evenly distributed within these branches.

The question about the effect of industrial diversity vs specialisation is no doubt one of the most studied issue what comes to the agglomeration of firms and its effects on regional development (e.g. Beaudry and Schiffauerova 2009). The effect of industrial diversity is equally relevant question what comes to the labour mobility. We may assume that if the worker's skills and the firm's labour requirements are specific to an industry, then it will be easier to meet these needs in a location where the industry is concentrated. Thus regional specialisation will increase both worker's and firm's probability to find a right job and the right type of employee. It also reduces worker's risk of becoming unemployed in case of the company—establishment specific layoff or termination. On the other hand, in the case of the industry-specific shock, specialisation causes difficulties for worker to find a job if most of the employers in the region are in the same negatively shocked industry (Frenken et al. 2007). In that case industrial diversity would probably make it easier to find a new job from industries which are technologically close to each other. The effect of high-tech industrial structure on labour flows can also indicate how important firms see the knowledge flows across technology related industries.

Our fourth high-tech variable is the *Number of the high technology establishments* in the region. We can assume that the more similar type establishments there are (i.e. firms operate technologically related industries), the greater number of employment opportunities there will be for employees to switch the job (Beaudry and Schiffauerova 2009), and less likely will be movement to other regions. Findings from the Swedish data share this view (Eriksson et al. 2008).[8] As Duranton and Puga (2004, 22) have written: "…as the workforce grows and the number of firms increases the average worker is able to find an employer that is better match for its skills".

Apart from these four variables specific to the high-tech sectors, we have also used two additional variables to control for regional aggregate trends affecting these sectors. These variables are firstly the *Proportion of the workers who leave both the high-tech sector and region* and secondly the *Proportion of the workers who leave high-tech sectors*. These variables are both calculated as a percentage of the total high-tech labour force within the region and are calculated to control for any possible increased employment termination rates in one or more of the local high-tech industries which result in forced job changes. Even if it may sound obvious that these variables have a positive effect on labour mobility, it is important to control their separate role (i.e. not related to agglomeration or other regional effects) as a reason for labour mobility.

In terms of those variables which are specific to the region but independent of high-tech issues per se, we employ four independent explanatory variables.

Our first such variable is the *Urbanisation rate*. This variable is defined here as the share of the population of the region living in areas where more than 200 inhabitants live and where the distance between the houses is no more than 200 m. Given the low and highly skewed density geography of Finland, we take this as a better proxy for pop-

[8] Eriksson et al. (2008) have argued that in smaller regions (where the number of firms is pretty low in general) firms probably know and meet each other more frequently. This can promote intra-regional labour mobility as firms view workers from other local companies more attractive because of their local knowledge of norms and routines.

ulation density than the standard population density measures typically employed.[9] Arguments regarding urbanisation and population density suggest that they facilitate the diffusion of information on job opportunities, and therefore, this variable would be expected to be associated with greater local employment switching (Di Addario 2011). Earlier findings have shown that 'closeness' boosts mobility and that there is a potential of better labour market matches in dense urban labour markets (e.g. Glaeser and Maré 2001). Bleakley and Lin (2007) have received completely different results when studying regions in the USA. According to their studies, average labour mobility is actually lower in denser regions, at least between industries. Furthermore, the general argument is that congestion, i.e. negative externality of agglomeration increases, e.g. housing costs, and thereby would induce out-migration of the region. Whether these arguments are equally applicable to the low-density geography of Finland is as yet unknown.

The second region-specific variable that we control for is the *Proportion of the service establishments in the private sector.* This variable is expressed in terms of the difference between the regional value and the average value across all of the regions and is intended to measure the absorptive capacity of the region and its resilience to technological shocks. It can be taken as a rough proxy for the diversity of local recreational amenities too. According to so-called 'equilibrium' approach of migration (based on the work of Graves 1976, 1980, 1983), regional wage differences and other economic factors are only partially compensating for spatial variations in non-tradable non-economic factors (Biagi et al. 2011). Workers, especially skilled workers, are moving more and more to the cities and urban milieus which are "rich" and attractive in terms of natural environment, cultural and recreational/lifestyle amenities (Scott 2010; Kotkin 2000; Gottlieb 1995). Hansen and Niedomysl (2009) provide quite opposite findings compared to the general view. According to their results, workers' migration behaviour depends on their age. Young educated people move to high-ranking region, while older people move towards lower-ranking regions. After Graves (1980) which focused specifically on location-specific natural amenities, e.g. climate, number of other studies have considered other type of amenities including public services (Blomquist et al. 1988; Gyourko and Tracey 1991), well-developed markets for consumer goods (Hanson 2000) and social, cultural and skill-dependent amenities (Glaeser et al. 2001; Florida 2002; Herzog et al. 1986) as reasons for inter-regional migration flows. Latest findings from USA seem to suggest that non-economic factors are key drivers in influencing migration patterns (Biagi et al. 2011; Partridge 2010). However, findings of the role of amenities in labour mobility in general, i.e. natural, cultural and recreational amenities, are somewhat contradictory (e.g. Scott 2010; Glaeser et al. 2001; Herzog et al. 1986).

The third region-specific variable that we control for is the *Growth rate of the establishments in private sector*, and this is used as a proxy for the general economic conditions in a region.[10] A higher value for this variable should reflect local economic buoyance and might therefore be expected to be associated with less outward move-

[9] Unfortunately we do not have data available to measure the concentration of workplaces and use that as a proxy for urbanisation.

[10] This variable is not measured as a difference to the regional average but our tests demonstrate that it does not matter whether we use difference values or levels values.

ments from the region. Following Scott (2010, 50) "Positive business conditions and prospects are no doubt especially important in attracting highly skilled workers to any given area."

In contrast, our fourth regional control variable which is the *Proportion of the unemployed people relative to the total employed people* might be expected to produce the opposite effect. A higher value for this last variable would reflect weak local demand conditions and might therefore be expected to be associated with greater movements away from the region (e.g. Finnie 2004).

The summary statistics and the correlation matrix regarding all of the explanatory variables are presented in Appendix Tables 7 and 8.[11]

Our modelling approach is the following. We start with the three different binary dichotomous logit models which are aimed at identifying whether there are similarities or differences between the inter-firm, inter-regional and inter-sectoral employment mobility patterns. As we see below our results demonstrate that the influences on these three distinct types of employment mobility patterns are quite different and discussions about high-tech worker 'mobility' are rather too general to be entirely meaningful. For this reason we then move on to a discussion of the results from the multinomial analysis which examines the influences on the five different individual categories of employment mobility behaviour which combine different combinations of inter-firm, inter-regional and inter-sectoral employment movements. Again, we see that these differences are very marked. Finally, on the basis of these observations, we employ an ordered logit model in order to provide an overall picture to these patterns. The results produce a consistent picture which is quite different to many of the assumptions implicit in much of the existing literature.

4 Estimation results

In the three binary logit models Models A–C, we aggregate labour movements in a following way. In Model A we estimate the likelihood of employees *staying* in their job versus employees who *change* their job; in Model B we estimate the likelihood of workers *staying* in a region versus workers who *change* their region of employment; and finally in Model C we estimate the likelihood of workers *staying* in a same industry versus workers who *change* the industry. These three dichotomous logit models are then followed by a multinomial logit model (Model D) and an ordered logit model (Model E). The aim of the three dichotomous models is to capture the major features of the three very different aggregated forms of employment mobility, namely inter-firm (within the region), inter-regional and inter-sectoral mobility. These are followed by the multinomial model in which we explicitly distinguish between each of the five mobility categories 1–5 listed above to see to what extent the major influences on

[11] We have checked how the possible correlations between the independent variables affect results. Various estimation results show that results and conclusions remain the same as shown in this paper. For instance, results do not change significantly if we leave, e.g. "the number of high-tech establishments" variable away from the estimations. We also ran the reduced form estimations, where we left variables out one by one (based on p-values) and all variables which are statistically significant stay significant and their signs do not change.

them differ. These four models paint a picture of heterogeneity, whereby we cannot simply speak of worker 'mobility', because the impacts of the different variables on the different forms of employment mobility behaviour, differ so significantly. Finally, given this heterogeneity, in order to provide the most parsimonious picture we employ the ordered logit model which is constructed on the basis of ascending degrees of mobility whereby higher values are accorded to more fundamental and challenging forms of mobility. In all forms of all models the dependent variables are based on the outflows of employees across high-tech industries and regions.

All estimations have been undertaken so as to control for the overdispersion which is quite common in these kinds of datasets (Collett 2003).[12]

We begin with our three dichotomous logit models examining the major influences on inter-firm mobility, inter-regional mobility and inter-sectoral mobility.

The first column in Table 4 presents the results of the first dichotomous logit Model A which estimates the likelihood of inter-firm mobility, independently of the destination. As expected, greater levels of agglomeration–urbanisation have a positive and significant effect on mobility (Glaeser and Maré 2001). High levels of high-tech diversity, regional high-tech wage levels and economic growth also all tend to be associated with greater employment mobility. In contrast, high levels of service activities tend to reduce mobility as does high local levels of high-tech specialisation. These results, however, raise the question to what extent they are related to only inter-regional or inter-industrial movement, or whether they are actually related to both types of labour mobility.

The second column in Table 4 presents the results of the second dichotomous logit Model B where we look at the likelihood of inter-regional mobility, having excluded those workers who do not change their job.[13] As expected, lower levels of inter-regional mobility amongst high technology workers are associated with higher numbers of such establishments in the local economy. The growth rate of establishments is in turn associated with greater inter-regional mobility. At the same time, interestingly, features such as high-tech specialisation, sectoral diversity and urbanisation and unemployment rates play no statistically significant role in determining inter-regional employment mobility.

The third column in Table 4 presents the results of the third dichotomous logit Model C where we examine the likelihood of employment mobility between high-tech sectors. Unemployment is associated with greater inter-sectoral mobility as are the levels of regional high-tech specialisation.[14]

[12] If the estimate of dispersion after fitting (measured by the deviance or Pearson's chi-square divided by the degrees of freedom) is >1, then we have reason to believe that data might be overdispersed. Without adjusting for the overdispersion, the standard errors are likely to be underestimated, causing the Wald tests to be too very sensitive. The only thing which will be different to the normal formation of point estimates (when we control the overdispersion) is that we shall make all conclusions little bit more cautiously since we scale the standard errors upwards.

[13] The average marginal effects of the variables on probability of changing the region as well as the marginal effect at the mean values of the variables are presented in the "Appendix" (Table 9).

[14] The average marginal effects of the variables on probability of changing the sector and the marginal effect at the mean values of the variables are presented in the "Appendix" (Table 10).

Table 4 Results of the logit Models A, B and C (dependent variables, see notes on below)

Variable (regional variables)	The coefficients of Model A (*p* value in parenthesis)	The coefficients of Model B (*p* value in parenthesis)	The coefficients of Model C (*p* value in parenthesis)
Intercept/constant	−5.1081 (<.0001)***	−0.0692 (0.9514)	−5.2153 (0.0027)***
Urbanisation rate	0.0230 (0.0003)***	0.0142 (0.2074)	0.0178 (0.2821)
Proportion of the service establishments (private sector) (*difference to the average across regions*)	−0.0273 (0.0283)**	−0.0026 (0.9067)	−0.0184 (0.5209)
Growth rate of the establishments (total in private sector)	0.0794 (0.0577)*	0.1883 (0.0121)**	−0.1239 (0.2254)
Unemployment (*difference to the average across regions*)	0.0135 (0.2109)	−0.0244 (0.2315)	0.0556 (0.0286)**
Location quotient of the high-tech sector (employment)	−0.2645 (<.0001)***	−0.0073 (0.4876)	0.6548 (<.0001)***
Regional wage in the high-tech sector (*difference to the median across regions, see note*)	0.0584 (0.0366)**	−0.0309 (0.5414)	−0.0643 (0.3646)
Diversity of the high-tech sector, (Shannon index, nine industries)	1.1301 (0.0008)***	0.4464 (0.4524)	0.4945 (0.5741)
Number of the high-tech establishments [in logarithmic (ln) scale]	−0.0478 (0.3988)	−0.4056 (0.0002)***	0.1876 (0.2546)
Proportion of the workers, who leave high-tech sector and region (percentage of the total high-tech labour)		−0.0229 (0.7808)	
Proportion of the workers, who leave high-tech sector and region (percentage of the total high-tech labour)			0.0296 (0.5416)
Scale (see note)	2.6938	2.3498	2.2474

Table 4 continued

Variable (regional variables)	The coefficients of Model A (*p* value in parenthesis)	The coefficients of Model B (*p* value in parenthesis)	The coefficients of Model C (*p* value in parenthesis)
Number of obs.	155,477 (0 = 141,866, 1 = 13,611)	13,611 (0 = 9648, 1 = 3963)	13,611 (0 = 10,648, 1 = 2963)

SAS is modelling the probability that dependent variable = 1
The scale parameter was estimated by the square root of DEVIANCE/DOF. The covariance matrix has been multiplied by the heterogeneity factor (Deviance/DF)
The median of the regional wage in the high-tech sector is almost the same as an average wage
Logit Model A (dependent variable: 0 = remain in the same high-tech firm, 1 = changes the firm within the region within the same high-tech industry, or changes the region within the same high-tech industry, or changes the high-tech industry within the same region, or changes the high-tech industry and the region)
Logit Model B (dependent variable: 0 = remain in the same region, 1 = change the region) (estimations exclude workers who remain in a same high-tech firm in a region)
Logit Model C, (dependent variable: 0 = remain in the same high-tech industry, 1 = change the high-tech industry) (estimations exclude workers who remain in a same high-tech firm in a region)
*, ** and *** Significance at the level of 10, 5 and 1 % level, respectively

The widely differing results of the three dichotomous logit Models A–C suggest that there are very different influences on inter-firm, inter-regional and inter-sectoral employment mobility. As such, discussions regarding the 'mobility' of high-tech workers between jobs are far too general to be meaningful, because it depends on what type of mobility we are actually considering. As yet, no papers we are aware of have explicitly examined the influences on these different types of employment mobility, particularly for high-tech sectors. In order to deepen our analysis of labour mobility while explicitly allowing for the heterogeneity of employment mobility patterns, we therefore now utilise a multinomial logit model whose individual response categories reflect the five different employment mobility categories 1–5 described above, with category 1 being used as the omitted baseline category.

The first columns in Table 5 reports the results of the multinomial logit Model D. As we see urbanisation and the degree of local high-tech diversity are positively associated with all forms of mobility 2, 3 and 4. In contrast, the total share of service sector establishments in the economy is negatively associated (even if statistical significance is quite low) with mobility categories 2, 3 and 4. Meanwhile, the regional location quotient of high-tech industries is negatively associated with inter-firm employment changes within the same sector (both within and between regions) but positively associated with local changes between sectors.

The various other variables display differing impacts on the different migration categories 2, 3 and 4. Both unemployment and the number of high-tech establishments are positively associated with migration category 4. The growth of private sector establishments is positively and the number of high-tech establishments negatively associated with migration category 3; and the local regional high-tech wage is positively associated with category 2 migration.

Finally, category 5 migration (changing both region and high technology employment sector), which in many ways is the most radical and challenging form of employment migration behaviour, is positively associated (at the 10 % level) with

Table 5 Results of the multinomial logit model (Model D) and ordered logit model (Model E)

Variable (regional variables)	The coefficients of MNL Model (D) (*p* value in parenthesis) categories				The coefficients of ordered logit model (E) (*p* value in parenthesis) categories			
	2	3	4	5	2	3	4	5
Intercept	−5.7862	−6.31879	−12.5321	−8.9620	−5.2803	−6.0842	−6.8798	−8.6476
	(<.0001)***	(<.0001)***	(<.0001)***	(<.0001)***	(<.0001)***	(<.0001)***	(<.0001)***	(<.0001)***
Urbanisation rate	0.0153	0.0336	0.0496	0.0349			0.0234	
	(0.0382)**	(<.0001)***	(0.0040)***	(0.0945)*			(0.0007)***	
Proportion of the service establishments	−0.0268	−0.0284	−0.0587	−0.0624			−0.0272 (0.0407)**	
(private sector) (*difference to the average across regions*)	(0.0559)*	(0.0858)*	(0.0569)*	(0.1459)			(0.0948)	
Growth rate of the establishments	0.0397	0.2000	−0.0857	0.1394			0.0792*	
(total in private sector)	(0.2782)	(0.0004)***	(0.4569)	(0.3411)			(0.0948)	
Unemployment rate	0.0151	0.0012	0.0795	0.0397			0.0137	
(*difference to the average across regions*)	(0.2177)	(0.9353)	(0.0030)***	(0.2782)			(0.2488)	
Location quotient of the high-tech sector	−0.4327	−0.3358	0.3010	−0.0334			−0.2519	
(employment)	(<.0001)***	(<.0001)***	(0.0262)**	(0.8405)			(<.0001)***	
Regional wage in the high-tech sector	0.0811	0.0385	−0.0229	0.0273			0.0575	
(*difference to the median across regions, see note*)	(0.0113)**	(0.2818)	(0.7725)	(0.7615)			(0.0626)*	

Table 5 continued

Independent variables	The coefficients of MNL Model (D) (*p* value in parenthesis) categories				The coefficients of ordered logit model (E) (*p* value in parenthesis) categories			
	2	3	4	5	2	3	4	5
Diversity of the high-tech sector	1.0813	1.3298	1.8924	1.8609			1.13653	
(Shannon index, nine industries)	(0.0046)***	(0.0024)***	(0.0550)*	(0.0997)*			(0.0010)***	
Number of the high-tech establishments	0.0751	−0.2941	0.3082	−0.2746			−0.0493	
[in logarithmic (ln) scale]	(0.2684)	(0.0002)***	(0.0575)*	(0.1685)			(0.4474)	
Proportion of the workers, who leave high-tech sector and region	0.0276	−0.0035	−0.0557	0.0232			0.0071	
(*percentage of the total high-tech labour*)	(0.6110)	(0.9533)	(0.7171)	(0.8749)			(0.8922)	
The covariance matrix has been multiplied by the heterogeneity factor (Deviance/DF)	4.7810						2.9794	
Number of obs.	155,477 (1 = 141,866, 2 = 7199, 3 = 3449, 4 = 2449, 5 = 514)							

SAS is modelling the probabilities of the levels of dependent variable categories having higher values. The scale parameter was estimated by the square root of DEVIANCE/DOF. The covariance matrix has been multiplied by the heterogeneity factor (Deviance/DF)

The median of the regional wage in the high-tech sector is almost the same as an average wage. Multinomial logit model: Dependent variable gets the following values: 1 = remain in the same high-tech firm in the region, 2 = change the high-tech firm within the region within the same high-tech industry, 3 = change the region within the same high-tech industry, 4 = change the high-tech industry within the same region, 5 = change the high-tech industry and the region. Ordered logit model: Dependent variable gets the following values: 1 = remain in the same high-tech firm in the region, 2 = change the high-tech firm within the region within the same high-tech industry, 3 = change the region within the same high-tech industry, 4 = change the high-tech industry within the same region, 5 = change the high-tech industry and the region

*, ** and *** Significance at the level of 10, 5 and 1 % level, respectively

Table 6 Summary table: Statistically significant variables in different models. Labour categories: 1 = remain in the same high-tech firm in the region, 2 = change the high-tech firm within the region within the same high-tech industry, 3 = change the region within the same high-tech industry, 4 = change the high-tech industry within the same region, 5 = change the high-tech industry and the region

Variable (regional variables)	Model A (1 vs 2-5)	Model B (Change the region, i.e. 2 + 4 vs 3 + 5) (excludes cat 1)	Model C (Change the HT-industry) 2 + 3 vs 4 + 5) (excludes cat 1)	Ordered Logit (Model E)	Multinomial Logit (Model D)	
Urbanisation rate	+++			+++	cat 5	+
					cat 4	+++
					cat 3	+++
					cat 2	++
Proportion of the service establishments (private sector) *(difference to the average across regions)*	−−			−−	cat 5	
					cat 4	−
					cat 3	−
					cat 2	−
Growth rate of the establishments (total in private sector)	+	++		+	cat 5	
					cat 4	
					cat 3	+++
					cat 2	

Table 6 continued

Variable (regional variables)	Model A (1 vs 2-5)	Model B (Change the region, i.e. 2 + 4 vs 3 + 5) (excludes cat 1)	Model C (Change the HT-industry) 2 + 3 vs 4 + 5) (excludes cat 1)	Ordered Logit (Model E)	Multinomial Logit (Model D)	
Unemployment (*difference to the average across regions*)			++		cat 5	
					cat 4	+++
					cat 3	
					cat 2	
Location quotient of the high technology sector (employment)	−−−		+++	−−−	cat 5	
					cat 4	++
					cat 3	−−−
					cat 2	−−−
Regional wage in the high-technology sector (*difference to the* ***median*** *across regions*)	++			+	cat 5	
					cat 4	
					cat 3	
					cat 2	++

Table 6 continued

Variable (regional variables)	Model A (1 vs 2-5)	Model B (Change the region, i.e. 2 + 4 vs 3 + 5) (excludes cat 1)	Model C (Change the HT-industry) 2 + 3 vs 4 + 5) (excludes cat 1)	Ordered Logit (Model E)	Multinomial Logit (Model D)	
Industrial diversity of the high technology sector, (Shannon index, 9 industries)	+++			+++	cat 5	+
					cat 4	+
					cat 3	+++
					cat 2	+++
Number of the high technology establishments (in logarithmic (ln) scale)		−−−			cat 5	
					cat 4	+
					cat 3	−−−
					cat 2	
Proportion of the workers, who leave high technology **sector and region** (*percentage of the total high technology labour*)	*not used*		*not used*		cat 5	
					cat 4	
					cat 3	
					cat 2	

Table 6 continued

Variable (regional variables)	Model A (1 vs 2-5)	Model B (Change the region, i.e. 2 + 4 vs 3 + 5) (excludes cat 1)	Model C (Change the HT-industry) 2 + 3 vs 4 + 5) (excludes cat 1)	Ordered Logit (Model E)	Multinomial Logit (Model D)
Proportion of the workers, who leave high technology **sector** (*percentage of the total high technology labour*)	*not used*	*not used*		*not used*	*not used*

Note: +/−, ++/−− and +++/−−− indicate significance at the level of 10%, 5% and 1% level as well as sign of the variable, respectively both urbanisation and the diversity of the high-tech sector in the region. No other explanatory variables offer any explanatory power regarding this particular form of employment mobility.

As we see, the impacts of different variables on employment mobility are both strongly and differently felt by the four distinct categories of mobility. As already mentioned, there is no simple picture of high-tech worker 'mobility' because it depends on which specific type of employment mobility we are interested in. The only sense in which it would appear that we can talk of general overall impacts on 'mobility', whereby 'mobility' here comprises all four of the distinct employment mobility categories 2–5, is where we are discussing the effects of urbanisation and diversity. These are the two explanatory variables that have clear and consistent impacts on all forms of mobility.

The last column in Table 5 reports the results of our ordered logit models which are constructed on the basis of ascending degrees of employment migration difficulty associated with the employment migration categories 1–5 respectively.[15] In other words the model estimates the degree of employment mobility. The aim here is to provide the most parsimonious picture of employment migration patterns, given the heterogeneity described above. As we see, increasing migration effects are positively associated with the levels of local urbanisation, economic growth, the scale of local sectoral diversity, the regional high-tech wage, and negatively associated with the size of the local service sector and the degree of high-tech specialisation in the region. The other variables are insignificant in their effects.

In order to synthesise the wide-ranging information derived from our various empirical results Table 6 provides a summary table which allows for a comparison between the different models. What becomes immediately obvious is that the results for Model A and the Ordered Logit Model E are basically identical. In other words, the factors which encourage mobility also influence the degree of employment mobility. In contrast, the results of Models B and C are mutually exclusive, which suggest that the factors determining employment mobility between sectors are totally different to the factors determining employment mobility between regions. This finding is also largely borne out by the multinomial results which also show differing effects for those categories which combine inter-sectoral and inter-regional movements.

5 Conclusions

Our intention in this paper has been to identify the different types of patterns and channels of labour mobility operating within and between different high-tech industrial clusters. There are several conclusions which emerge from this research. As our analysis has clearly demonstrated, we cannot talk simply of high-tech worker

[15] Because of technological specificities, we assume that switching sector is more difficult than changing regional location, thereby justifying the ranking of our categories 3 and 4. Moreover, this is also borne out by the numbers of actual movements, with inter-regional movements between firms within the same high-tech sector outnumbering employment movements between firms in different sectors but within the same region.

‘mobility’. In addition to non-movers, there are also four distinct types of employment movers (denoted as categories 2–5 here). There is mobility between sectors, between regions, or combinations of sectors and regions and the effects of each of the explanatory variables in each type of mobility differ markedly. Urbanisation and local diversity are found to be associated with greater movements between local firms in the same sector or different sectors in the same place. However, differently to many discussions regarding agglomeration, increasing urbanisation and diversity are also associated with greater degrees of mobility of all forms, including mobility *away* from the region. In other words, urbanisation and diversity are also associated with greater movements to *other* places as well as to other sectors. So we may argue that in addition to the earlier findings in the literature that ‘closeness’ boosts mobility because there is a potential for better labour market matches in dense urban labour markets (Glaeser and Maré 2001; Eriksson et al. 2008) urbanisation also increases the probability of individuals moving away from the region, even if you stay employed on the high-tech sector (either same or another industry). This same conclusion also holds for the effect of high-tech diversity. Both urbanisation and sectoral diversity therefore promote mobility outside of the region as well as within it. On the other hand, regional specialisation tends to be associated with generally lower levels of employment mobility, although this is not always the case. This result is largely due to it being negatively related to inter-firm mobility in general, although specialisation encourages local inter-sectoral employment switching. As such, specialisation tends to keep people in a region, but increases inter-industry labour mobility. Unsurprisingly, the number of high-tech establishments reduces the probability of an individual moving away from the region and also increases the probability that an individual will change their local industry of employment. Yet, and maybe rather surprisingly, it has no effect on local intra-industry labour mobility. At the same time, the overall economic conditions will play a role. Higher salaries increase the levels of labour mobility but only in the easiest form of mobility, i.e. job changes within the same individual high-tech industry and within the same region, and are not related to other forms of mobility.

Taken together, these various results suggest that we cannot simply talk about the local employment ‘mobility’ of workers in regions due to features such as urbanisation, diversity or specialisation. The reason is that urbanisation and diversity are not only associated with local inter-firm mobility but also greater levels of inter-regional and inter-sectoral mobility. In the case of the Finnish high-tech sectors, these non-local forms of employment mobility have already been shown to be associated with increased innovation performance (Simonen and McCann 2008, 2010) relative to local labour mobility. Similar type of findings has been achieved with the Swedish and Danish data (Boschma et al. 2009; Timmermans and Boschma 2014). However, identifying the subtle and differentiated effects associated with the various sub-categories of employment mobility has only been possible because of the level of detail of our employment mobility dataset. To explain these mechanisms in greater detail will require the use of individual-specific and firm specific-data, and these are issues for further research.

Appendix

See Tables 7, 8, 9 and 10.

Table 7 Values of the explanatory variables

Variable	N	Mean	SD	Minimum	Maximum
Urbanisation rate	64	72.31	14.18	41.44	99.62
Proportion of the service establishments (private sector) (*difference to the average across regions*)	64	0.46	6.32	−13.91	13.87
Growth rate of the establishments (*total in private sector*)	64	1.27	1.36	−2.58	5.23
Unemployment rate (*difference to the average across regions*)	64	0.29	5.19	−12.33	18.01
Location quotient of the high-tech sector (*employment*)	64	0.48	0.56	0.032	3.38
Regional wage in the high-tech sector (*difference to the average across regions*)	64	0.13	2.29	−6.49	5.58
Industrial diversity of the high-tech sector, (*Shannon index, nine industries*)	64	1.15	0.18	0.69	1.55
Number of the high-tech firms [*in logarithmic (ln) scale*]	64	4.37	1.22	2.56	8.67
Proportion of the workers, who leave high-tech sector and region (*percentage of the total high-tech labour*)	64	3.03	1.501	0.52	8.86
Proportion of the workers, who leave high-tech sector (*percentage of the total high-tech labour*)	64	8.96	4.23	2.45	33.33

Table 8 Correlation matrix of the explanatory variables

Variable	Urbanisation rate	Proportion of the service establishments (private sector) (*difference to the average across regions*)	Growth rate of the establishments (total in private sector)	Unemployment rate (*difference to the average across regions*)	Location quotient of the high-tech sector (employment)
Urbanisation rate	1.000				
Proportion of the service establishments (private sector) (*difference to the average across regions*)	0.609	1.000			
Growth rate of the establishments (total in private sector)	0.012	−0.065	1.000		
Unemployment rate (*difference to the average across regions*)	−0.245	0.260	−0.213	1.000	
Location quotient of the high-tech sector (employment)	0.454	0.362	0.242	−0.152	1.000
Regional wage in the high-tech sector (*difference to the average across regions*)	0.586	0.401	0.210	−0.326	0.394
Industrial diversity of the high-tech sector, (Shannon index, nine industries)	0.153	0.269	−0.079	0.058	0.276
Number of the high-tech firms [in logarithmic (ln) scale]	0.784	0.531	0.263	−0.248	0.594
Proportion of the workers, who leave high-tech sector and region (*% of the total high-tech labour*)	−0.254	−0.303	−0.012	−0.001	−0.286
Proportion of the workers, who leave high-tech sector (*% of the total high-tech labour*)	−0.133	−0.106	−0.121	0.141	−0.191

Table 8 continued

Variable	Regional wage in the high-tech sector (*difference to the average across regions*)	Industrial diversity of the high-tech sector, (Shannon index, nine industries)	Number of the high-tech firms [in logarithmic (ln) scale]	Proportion of the workers, who leave high technology sector and region (*% of the total high-tech labour*)	Proportion of the workers, who leave high technology sector (*% of the total high-tech labour*)
Urbanisation rate					
Proportion of the service establishments (private sector) (*difference to the average across regions*)					
Growth rate of the establishments (total in private sector)					
Unemployment rate (*difference to the average across regions*)					
Location quotient of the high-tech sector (employment)					
Regional wage in the high-tech sector (*difference to the average across regions*)	1.000				
Industrial diversity of the high-tech sector, (Shannon index, nine industries)	0.049	1.000			
Number of the high-tech firms [in logarithmic (ln) scale]	0.590	0.245	1.000		
Proportion of the workers, who leave high-tech sector and region (*% of the total high-tech labour*)	−0.317	−0.313	−0.343	1.000	
Proportion of the workers, who leave high-tech sector (*% of the total high-tech labour*)	−0.178	−0.220	−0.219	0.484	1.000

Number of observation is 64

Table 9 Average marginal effects on probability of changing the region and marginal effect at the mean values of the variables (Model B)

Variable	N	Mean	SD	Minimum	Maximum	Marginal effect at the mean value of the variable
Urbanisation rate	64	0.0034	0.0002	0.0022	0.0035	0.0035
Proportion of the service establishments (private sector) (*difference to the average across regions*)	64	−0.0006	0.00004	−0.0006	−0.0004	−0.0006
Growth rate of the establishments (*total in private sector*)	64	0.0452	0.0031	0.0289	0.0471	0.0467
Unemployment rate (*difference to the average across regions*)	64	−0.0058	0.0004	−0.0061	−0.0037	−0.0060
Location quotient of the high-tech sector (*employment*)	64	−0.0161	0.0011	−0.0168	−0.0103	−0.0167
Regional wage in the high-tech sector (*difference to the average across regions*)	64	−0.0074	0.0005	−0.0077	−0.0047	−0.00771
Industrial diversity of the high-tech sector, (*Shannon index, nine industries*)	64	0.1070	0.0074	0.0686	0.1116	0.1107
Number of the high-tech firms [*in logarithmic (ln) scale*]	64	−0.0972	0.0067	−0.1014	−0.0623	−0.1006
Proportion of the workers, who leave high-tech sector and region (*percentage of the total high-tech labour*)	64	−0.0055	0.0004	−0.0057	−0.0035	−0.0057

Table 10 Average marginal effects on probability of changing the sector and marginal effect at the mean values of the variables (Model C)

Variable	N	Mean	SD	Minimum	Maximum	Marginal effect at the mean value of the variable
Urbanisation rate	64	0.0018	0.0008	0.0003	0.0040	0.0017
Proportion of the service establishments (private sector) (*difference to the average across regions*)	64	−0.0019	0.0008	−0.0041	−0.0003	−0.0018
Growth rate of the establishments (*total in private sector*)	64	−0.0126	0.0056	−0.02798	−0.0022	−0.0118
Unemployment rate (*difference to the average across regions*)	64	0.0056	0.0025	0.0009	0.0125	0.0053
Location quotient of the high-tech sector (*employment*)	64	0.0667	0.0298	0.0114	0.1475	0.0626
Regional wage in the high-tech sector (*difference to the average across regions*)	64	−0.0066	0.0029	−0.0144	−0.0011	−0.0061
Industrial diversity of the high-tech sector, (*Shannon index, nine industries*)	64	0.0503	0.0225	0.0086	0.1113	0.0472
Number of the high-tech firms [*in logarithmic (ln) scale*]	64	0.0191	0.0085	0.0033	0.0422	0.0179
Proportion of the workers, who leave high-tech sector (*percentage of the total high-tech labour*)	64	0.0030	0.0013	0.0005	0.0067	0.0028

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