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Local high-tech job multipliers in Europe

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Abstract

Examining employment growth in local labor markets across Europe, this article finds that each worker in a high-skilled occupation creates up to five extra jobs in local less-skilled-intensive services in the same region. However, it is also shown that there exist persistent differences in the size of this local high-tech job multiplier across regions. In particular, we find that the multiplier is larger in regions with higher immigration, an abundance of less-skilled workers, and lower gross output per capita. At the country level, we also show that this results in local high-tech job multipliers that are larger in Southern European countries than in the rest of Europe.

JEL classification: J21, J23, R12

1. Introduction

For US cities, the importance of local job multipliers was first shown by Moretti (2010). He estimates that for every job created in manufacturing, there are 1.5 jobs created in construction and services in a city. This multiplier increases to 2.5 when only considering the creation of skilled jobs in manufacturing. Moreover, Moretti (2010) finds a local job multiplier of 5 for an additional job in high-tech sectors. In related work, Moretti and Wilson (2014) find an even larger high-tech job multiplier for jobs created by biotech companies. Finally, Moretti and Thulin (2013) use variation across 72 local labor markets in Sweden and find that each job created in manufacturing generates 0.5 jobs in sectors producing local goods and services. The local multiplier for an additional skilled job in manufacturing is 2.8, and for an additional job in high-tech manufacturing is 1.1. A simple way to explain the existence of these multipliers, it is argued, is that innovation and globalisation increase the demand for workers in high-tech and tradable sectors in a region. In turn, these workers generate other jobs outside these sectors in that region, resulting in a local job multiplier.[1]

This article adds to this literature in two ways. First, because there currently exists little evidence about local job multipliers for Europe, this article estimates local high-tech job multipliers using variation across 227 regions in the

1 Other job multipliers not directly related to the impacts of innovation and globalization have been examined. For example, Faggio and Overman (2014) consider the impact on UK local labor markets from creating public sector jobs. They find that public sector employment has no identifiable effect on the level of private sector employment but that it does affect the sectoral composition of the private sector. Specifically, they find that each additional public sector job creates 0.5 jobs in construction and services while crowding out 0.4 jobs in manufacturing.

Table 1. High-tech components

Panel A: High-tech industries (NACE rev. 1.1)
High-tech manufacturing
Pharmaceuticals, medicinal chemical, and botanical products (24.4)
Office machinery and computers (30)
Radio, television, and communication equipment and apparatus (32)
Medical, precision and optical instruments, watches and clocks (33)
Aircrafts and spacecrafts (35.3)
High-tech knowledge-intensive services
Post and telecommunications (64)
Computer and related activities (72)
Research and development (73)
Panel B: STEM occupations (ISCO-88)
Physical and life sciences
Physicists, chemists, and related professionals (211)
Life science professionals (221)
Life science technicians, and related associate professionals (321)
Computer and mathematical sciences
Mathematicians, statisticians, and related professionals (212)
Computer professionals (213)
Computer associate professionals (312)
Engineering and related
Architects, engineers, and related professionals (214)
Physical and engineering science technicians (311)

NACE: Nomenclature statistique des activités économiques dans la Communauté européenne, ISCO: International Standard Classification of Occupations.

European Union (EU)-27 between 2000 and 2011.[2] Second, this article uses a definition of high-tech employment that is complementary to existing measures. In line with existing measures, our definition of high-tech employment includes all workers employed in high-tech manufacturing, defined by a high ratio of R&D expenditure over value added, and all workers employed in high-tech knowledge-intensive services, defined by a high fraction of tertiary educated workers. In contrast to existing measures, our definition of high-tech employment also includes all skilled workers in Science, Technology, Engineering, and Maths (STEM) occupations that are not employed in high-tech manufacturing or high-tech knowledge-intensive service sectors. As will become clear below, including these STEM occupations in our definition of high-tech jobs is important in understanding local high-tech job multipliers.

The remainder of this article is organised as follows. Section 2 describes the data. Section 3 provides some summary statistics about overall and high-tech employment growth in Europe between 2000 and 2011. In Section 4 the local high-tech job multiplier is estimated, and Section 5 explores regional variations in the multiplier. Finally, Section 6 concludes.

2. Data

In line with standard measures of high-tech employment, we begin by counting all workers employed in high-tech sectors listed in Panel A of Table 1. This follows Eurostat's definition of high-tech based on a firm's NACE code and includes high-tech manufacturing (e.g., the production of robots or airplanes) as well as high-tech knowledge-intensive services [e.g., Information and Communication Technology (ICT) consulting or the scientific research and development of new technologies]. Manufacturing sectors are labelled high-tech when they have a high degree of technological intensity, i.e., R&D expenditure over value added, while the knowledge intensity of a service is based

2 EU-27 refers to the European Union and its 27 member-states in 2011 and our precise definition of high-tech employment is given in Section 2 below. The time span is necessarily restricted to the period 2000–2011 due to several data limitations, see Annex A.

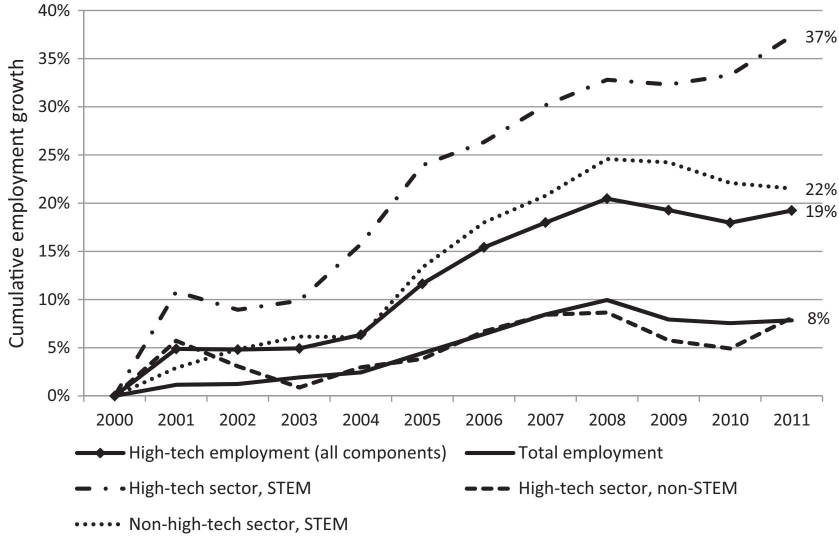

Figure 1. Cumulative employment growth: total versus high-tech components (in %, EU-27, 2000–2011).
Notes: In the years before total country coverage (2000-2004) EU-27 employment in the high-tech components is calculated as the employment share of the components in the covered countries multiplied by total EU-27 employment.

on its share of tertiary educated persons. Employment in high-tech sectors for each NUTS-2 region is available from Eurostat's Regional Science and Technology Statistics Database.[3]

In contrast to the traditional measures of high-tech employment discussed in the previous paragraph, we add all workers engaged in highly technical activities outside the high-tech sectors listed in Panel A of Table 1. In particular, we add all workers in STEM occupations employed in sectors not listed in Panel A of Table 1. These STEM occupations are listed in Panel B of Table 1 and follow the definition of the US Bureau of Labor Statistics in the United States.[4] For example, our definition of high-tech employment thereby also includes engineers in car manufacturing, computer programmers in retail trade, quantitative analysts in financial services, or statisticians in health-care administration. Employment in STEM occupations in Panel B of Table 1 is obtained from the European Union Labour Force Survey (ELFS) micro data set, and merged at the NUTS-2 level with the data for the high-tech industries from Panel A of Table 1.[5]

3. High-tech employment growth over time and across regions

The solid lines in Figure 1 show the cumulative percentage growth in total and high-tech employment in the EU-27 between 2000 and 2011: 19% versus 8%, respectively. Moreover, the dashed lines in Figure 1 show the importance of the different components in our definition of high-tech employment. The fastest job growth can be observed for STEM workers in high-tech sectors, growing by a cumulative 37% between 2000 and 2011. Also workers in STEM occupations outside high-tech sectors grew faster than overall high-tech employment, by 22% versus 19%, respectively, whereas employment of non-STEM workers in high-tech industries only increased at the pace of European-wide total employment, by 8% between 2000 and 2011. These figures clearly show the importance of the inclusion of STEM workers outside high-tech sectors, as employment in STEM occupations has been the main driver of total high-tech employment growth.

3 The NUTS classification (Nomenclature des Unités territoriales statistiques) is used to divide the European territory into regions of different population sizes, mainly for statistical and EU Regional Policy purpose.
4 See Hecker (2005).
5 For the UK we use the UK Labour Force Survey rather than the ELFS. Further details on the construction of the high-tech employment data set can be found in Appendix.

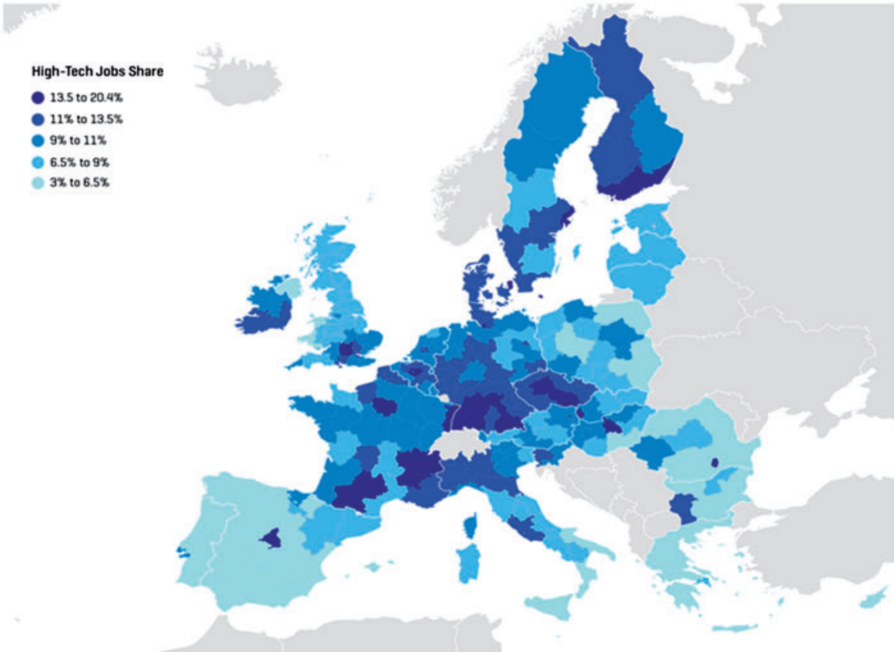

Figure 2. High-tech intensity per NUTS-2 region (in %, 2011).

The faster growth of high-tech than total employment implies that the share of high-tech in total employment increased over time from 9% in 2000 to 10% in 2011. The EU-wide high-tech employment share of 10% in 2011 masks large differences in high-tech intensity between countries and regions in Europe. To illustrate this, Figure 2 shows the high-tech employment shares for all EU NUTS-2 regions in 2011. While the regions in Western and Northern Europe generally have higher high-tech intensity, the share is much lower in some Southern and Eastern European regions. To illustrate this further, Table 2 gives the top (Panel A) and bottom (Panel B) 15 regions in terms of their high-tech employment share that are of sufficiently large size, i.e., with an employed population of at least one million in 2011. The top regions include large capital regions, such as Paris, London, Berlin and Stockholm, as well as regions with a strong sectoral specialization, such as Midi-Pyrenées (aerospace, ICT, and agro food) and Stuttgard (mechanical engineering). The lagging regions are mainly located in Southern Europe and Romania.

While high-tech employment grew in the large majority of European regions, it is interesting to see in which regions high-tech employment growth was strongest. For example, stronger growth in regions that initially already had higher shares of high-tech employment would suggest a lack of convergence in high-tech employment across regional labor markets in Europe. To see whether this is true, Panel A of Figure 3 shows the evolution between 2000 and 2011 of the interquartile range of high-tech employment shares across NUTS-2 regions, the larger NUTS-1 regions, and the EU countries.[6] Panel A of Figure 3 shows that the interquartile range in high-tech employment intensity between regions remained constant between 2000 and 2011, suggesting pervasive differences between regions, and between countries. To illustrate this further, Panel B of Figure 3 shows that the within-country interquartile range in high-tech employment shares across NUTS-2 and NUTS-1 regions within countries remained constant over time, suggesting that also within countries regional differences remained pervasive. In sum, what Figures 1–3 suggest is that European regions have been able to create high-tech jobs, but that these high-tech jobs remain highly concentrated in regionally clustered high-tech hubs.

6 Each country consists of several NUTS-1 regions of similar population size and each NUTS-1 region consists of several NUTS-2 regions of similar population size. The interquartile range is the difference between the 75th and 25th percentile of the high-tech employment share across regions. Using the standard deviation instead of the interquartile range gives qualitatively similar results.

Table 2. Top and bottom high-tech intensity regions (2011)

NUTS-2 region	Total employment in 2011 (1000 persons)	High-tech employment share in 2011 (%)
	Panel A: Top-15	
1. Stockholm (Sweden)	1101	18.0
2. Île de France (France)	5228	17.6
3. Bucuresti - Ilfov (Romania)	1058	15.7
4. Midi-Pyrénées (France)	1232	15.4
5. Karlsruhe (Germany)	1334	15.4
6. Etelä-Suomi (Finland)	1307	14.9
7. Rhône-Alpes (France)	2578	14.9
8. Oberbayern (Germany)	2241	14.4
9. Stuttgart (Germany)	1987	14.4
10. Közép-Magyarország (Hungary)	1243	14.3
11. Comunidad de Madrid (Spain)	2813	14.0
12. Freiburg (Germany)	1248	13.8
13. Berkshire, Buckinghamshire, Oxfordshire (United Kingdom)	1306	13.6
14. Köln (Germany)	1999	13.0
15. Lombardia (Italy)	4263	12.4
	Panel B: Bottom-15	
1. Centro Region (Portugal)	1103	3.6
2. Nord-Est (Romania)	1731	4.3
3. Norte (Portugal)	1695	4.7
4. Sud-Est (Romania)	1106	5.2
5. Andalucia (Spain)	2774	5.3
6. Communidad Valencia (Spain)	1889	5.5
7. Sud-Muntenia (Romania)	1306	5.6
8. Galicia (Spain)	1082	5.7
9. Sicilia (Italy)	1431	5.9
10. Nord-Vest (Romania)	1164	5.9
11. Puglia (Italy)	1232	6.2
12. Wielkopolskie (Poland)	1412	6.3
13. Sud-Vest Oltenia (Romania)	1024	6.5
14. Lietuva (Lithuania)	1369	6.6
15. Attiki (Greece)	1535	7.0

4. The local high-tech job multiplier

The local high-tech job multiplier is given by $\gamma > 0$ in:

$$\frac{\Delta L_{j,t}}{E_{j,t-s}} = \gamma \frac{\Delta H_{j,t}}{E_{j,t-s}} \tag{1}$$

with $\Delta L_{j,t}$ the absolute change in employment outside high-tech in NUTS-2 region j between periods t and $t-s$, $\Delta H_{j,t}$ the absolute change in high-tech employment in NUTS-2 region j between periods t and $t-s$, and $E_{j,t-s}$ total employment in NUTS-2 region j in period $t-s$.[7] Adding a country-time fixed effect, $F_{c,t}$, to control for country-wide shocks in employment between period t and $t-s$, we get:

$$\frac{\Delta L_{j,t}}{E_{j,t-s}} = \gamma \frac{\Delta H_{j,t}}{E_{j,t-s}} + F_{c,t} + \upsilon_{j,t}, \tag{2}$$

with $\upsilon_{j,t}$ an error term.

7 That is, $E_{j,t-s} = L_{j,t-s} + H_{j,t-s}$. We express high- and low-tech employment relative to total employment to avoid spurious positive correlation that might arise when using absolute values—see Peri and Sparber (2011) for details.

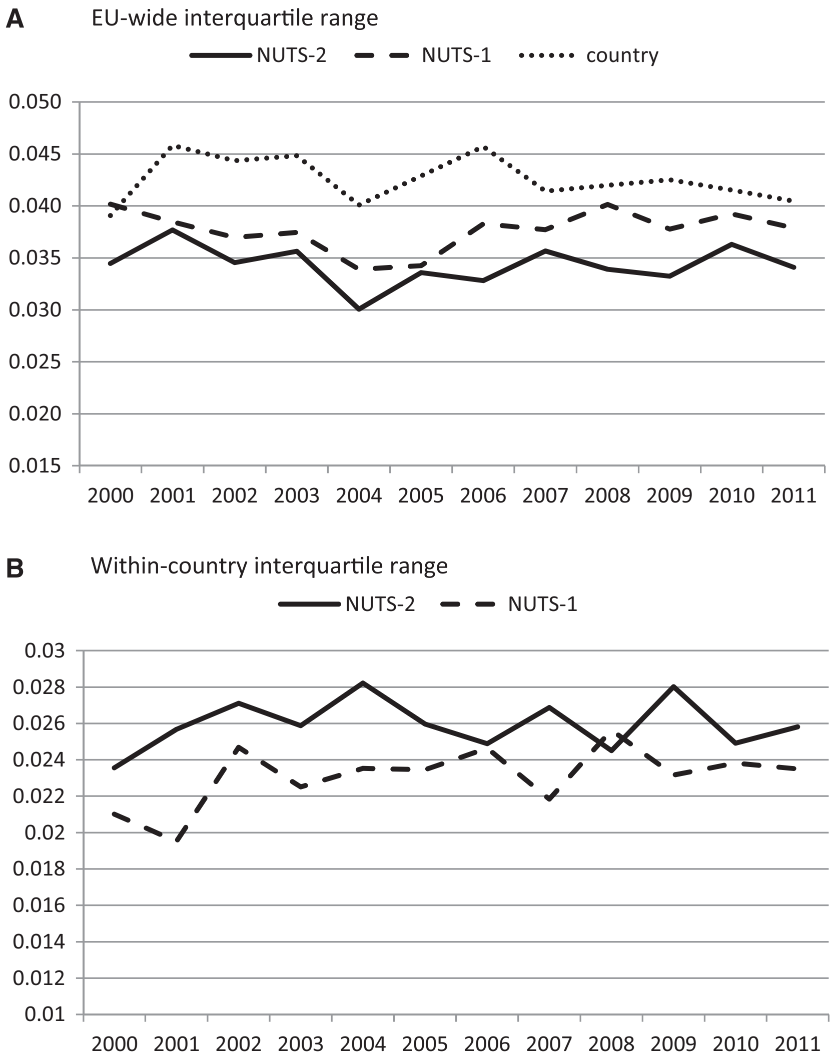

Figure 3. Interquartile range of high-tech intensity (2000–2011).
Notes: Only regions or countries with twelve annual observations are included. Within-country interquartile ranges in panel B are aggregated using employment weighted averages.

However, the interpretation of γ in equation (2) is not causal if, for example, there are regional level shocks that have an impact on both high-tech as well as other employment. To address this issue, we follow Moretti (2010) in constructing two Bartik instruments. A first instrument is given by:

$$\frac{\Delta \hat{H}^1_{j,t}}{E_{j,t-s}} = \frac{H_{j,t-s}}{E_{j,t-s}} \left[\frac{(H_{c,t} - H_{j,t}) - (H_{c,t-s} - H_{j,t-s})}{H_{c,t-s} - H_{j,t-s}} \right], \tag{3}$$

where the term in square brackets is the growth rate of high-tech employment in country c excluding region j. This growth rate is multiplied by region j's initial share of high-tech employment to get $\Delta \hat{H}^1_{j,t}/E_{j,t-s}$.[8]

8 van Dijk (2014) argues that Moretti (2010) overestimates the multiplier because of two reasons that we account for in our analysis. First, equation (2) uses changes in the *level* of employment to directly estimate the multiplier, whereas Moretti (2010) uses changes in the *log* of employment to estimate an elasticity instead. Moretti (2010) then multiplies this elasticity by the

Table 3. Multiplier regression—baseline results

Independent variable:	Dependent variable: Employment growth of non-STEM occupations in low-tech industries			
	OLS	IV		
		Equation (3)	Equation (4)	Equations (3) and (4)
	A. High-tech and STEM			
Employment growth of high-tech industries and STEM occupations	1.15*	4.40*	4.08*	3.94*
	(0.24)	(1.08)	(1.04)	(1.02)
		IV first-stage coefficients		
Equation (3)	–	0.70*	–	−0.36
		(0.10)		(0.43)
Equation (4)	–	–	0.73*	1.08*
			(0.10)	(0.42)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*46.63*	*51.70*	*28.56*
IV overidentification Chi-sq statistic	–	–	–	*3.65*
	B. High-tech industry			
Employment growth in high-tech industries	0.94*	4.73*	4.75*	4.88*
	(0.30)	(1.90)	(1.90)	(1.86)
		IV first-stage coefficients		
Equation (3)	–	0.74*	–	−7.66
		(0.14)		(9.67)
Equation (4)	–	–	0.75*	8.42
			(0.14)	(9.65)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*29.30*	*29.54*	*16.88*
IV overidentification Chi-sq statistic	–	–	–	*0.79*
	C. STEM occupations			
Employment growth in STEM occupations	1.31*	4.32*	4.90*	5.05*
	(0.32)	(1.52)	(1.46)	(1.45)
		IV first-stage coefficients		
Equation (3)	–	0.63*	–	−0.18
		(0.10)		(0.63)
Equation (4)	–	–	0.65*	0.83
			(0.11)	(0.63)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*35.88*	*36.66*	*18.23*
IV overidentification Chi-sq statistic	–	–	–	*5.28*

Notes: Standard errors clustered at the regional level, and * indicates significance at the 1% level. All IV first-stage *F*-statistics are significant at 1%, and none of the IV overidentification Chi-square statistics is. All regressions include country-year fixed effects. IV: Instrumental variables.

ratio of nonmanufacturing over manufacturing employment in the final period, $L_{j,t}/H_{j,t}$, to obtain an estimate of the multiplier. van Dijk (2014) argues that this leads to an overestimation of the multiplier because $L_{j,t}/H_{j,t} > L_{j,t-s}/H_{j,t-s}$ given the relative decline over time in manufacturing employment. Second, the right-hand side of equation (3) subtracts employment in region *j* from total employment, whereas Moretti (2010) does not exclude region *j* from total employment thereby making it more likely that the instrument is correlated with the endogenous variation in $\Delta H_{j,t}/E_{j,t-s}$ (especially when region *j* is relatively large in terms of employment). van Dijk (2014) argues that these two shortcomings in Moretti (2010) lead to an overestimation of the multiplier by about 50% (e.g., a multiplier of 1 instead 1.5).

Table 4. Multiplier regressions—different components (high-tech)

Independent variable:	OLS	IV		
		Equation (3)	Equation (4)	Equations (3) and (4)
	A. Dependent variable: Total employment growth in low-tech industries			
Employment growth in high-tech industries	0.85*	5.15*	5.16*	5.30*
	(0.32)	(2.01)	(2.01)	(1.97)
		IV first-stage coefficients		
Equation (3)	–	0.74*	–	−7.66
		(0.14)		(9.67)
Equation (4)	–	–	0.75*	8.42
			(0.14)	(9.65)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*29.30*	*29.54*	*16.88*
IV overidentification Chi-sq statistic	–	–	–	*0.71*
	B. Dependent variable: Employment growth of STEM occupations in low-tech industries			
Employment growth in high-tech industries	−0.85	0.41	0.41	0.41
	(0.61)	(0.18)	(0.18)	(0.17)
		IV first-stage coefficients		
Equation (3)	–	0.74*	–	−7.66
		(0.14)		(9.67)
Equation (4)	–	–	0.75*	8.42
			(0.14)	(9.65)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*29.30*	*29.54*	*16.88*
IV overidentification Chi-sq statistic	–	–	–	*0.04*

Notes: Standard errors clustered at the regional level, and * indicates significance at the 1% level. Independent variable is growth in high-tech employment. All IV first-stage *F*-statistics are significant at 1%, and none of the IV overidentification Chi-square statistics is. All regressions include country-year fixed effects.

To go even further, one could use the country-level changes for each of the different components of high-tech employment outlined in Figure 1:

$$\frac{\Delta\hat{H}^{2}_{j,t}}{E_{j,t-s}} = \sum_{i\in H}\frac{H_{i,j,t-s}}{E_{i,j,t-s}}\left[\frac{(H_{i,c,t}-H_{i,j,t})-(H_{i,c,t-s}-H_{i,j,t-s})}{H_{i,c,t-s}-H_{i,j,t-s}}\right], \tag{4}$$

where the different components i are STEM occupations in high-tech sectors, STEM occupations outside high-tech sectors, and non-STEM occupations in high-tech sectors. While similar to the instrument defined in equation (3), the instrument in equation (4) also accounts for differences in the composition of high-tech employment across regions.

Table 3 reports the results of estimating equation (2) using two 5-year differences for the periods 2000–2005 and 2005–2010. The first column in Table 3 uses ordinary least squares (OLS) to estimate equation (2), whereas the remaining columns show IV estimates using equations (3) and (4) as instruments for $\Delta H_{j,t}/E_{j,t-s}$ in equation (2). In particular, the second column of Table 3 only uses equation (3) as an instrument, and the third column of Table 3 only uses equation (4) as an instrument. Finally, the fourth column of Table 3 uses both instruments in equations (3) and (4) simultaneously. For the IV estimates, first-stage coefficients are reported together with the IV first-stage *F*-statistic which should be sufficiently large for the first-stage to be sufficiently strong. Because the last column uses both instruments jointly, Hansen's J Chi-square statistic for IV overidentification is reported which should be sufficiently small for the instruments to be valid.

The results in Panel A of Table 3 show that high-tech employment growth is associated with a significant positive multiplier for non-STEM jobs in low-tech sectors, both in the OLS and the IV regressions. The IV results, our preferred specification, show that each high-tech job is linked to between 3.9 and 4.4 non-STEM jobs in low-tech sectors, depending on the chosen instrument. These results suggest that high-tech job creation in a region has a strong positive spillover effect on other jobs in that region.

Table 5. Multiplier regressions—different components (STEM)

Independent variable:	OLS	IV		
		Equation (3)	Equation (4)	Equations (3) and (4)
	A. Dependent variable: Total employment growth in non-STEM occupations			
Employment growth in STEM occupations	1.43*	4.56*	5.19*	5.36*
	(0.33)	(1.55)	(1.49)	(1.48)
		IV first-stage coefficients		
Equation (3)	–	0.63*	–	−0.18
		(0.10)		(0.63)
Equation (4)	–	–	0.65*	0.83
			(0.11)	(0.63)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*35.88*	*36.66*	*18.23*
IV overidentification Chi-square	–	–	–	*5.98*
	B. Dependent variable: Employment growth of non-STEM occupations in high-tech industries			
Employment growth in STEM occupations	0.13*	0.23	0.29*	0.31*
	(0.04)	(0.10)	(0.10)	(0.10)
		IV first-stage coefficients		
Equation (3)	–	0.63*	–	−0.18
		(0.10)		(0.63)
Equation (4)	–	–	0.65*	0.83
			(0.11)	(0.63)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*35.88*	*36.66*	*18.23*
IV overidentification Chi-square	–	–	–	*3.89*

Notes: Standard errors clustered at the regional level, and * indicates significance at the 1% level. Independent variable is employment growth in STEM occupations. All IV first-stage *F*-statistics are significant at 1%, and none of the IV overidentification Chi-square statistics is. All regressions include country-year fixed effects.

Panels B and C of Table 3 repeat the analysis for the different components of our high-tech employment measure: Employment in traditional high-tech industries and employment in STEM occupations. The results in Panel B show that job creation in high-tech industries is associated with a local job multiplier of around 4.8. This definition of the high-tech job multiplier is closer in line with the definitions used in the earlier literature. In comparison to this literature, the estimates in Panel B of Table 3 are in the upper range of estimates found in Moretti (2010), Moretti and Wilson (2014) and van Dijk (2014) for the United States, and Moretti and Thulin (2013) for Sweden. When focussing on the STEM component of our definition which also includes STEM workers in low-tech sectors, Panel C shows that the STEM multiplier has a very similar value, ranging between 4.3 and 5. As both employment in high-tech industries and employment in STEM occupations are associated with strong multiplier effects, this confirms the importance of our complementarity definition of high-tech employment when understanding local high-tech job multipliers.

To get a better understanding of the channels through which the local multiplier operates, we repeat the analysis from Table 3 but using different dimensions of our employment data as dependent and independent variables. More specifically, Table 4 uses as the independent variable job creation in high-tech sectors, as was done in Panel B of Table 3. However, in contrast to Panel B of Table 3, Table 4 uses different dependent variables. Panel A of Table 4 uses total employment in low-tech industries, both in STEM and non-STEM occupations, whereas Panel B of Table 4 only uses employment growth of STEM occupations in low-tech sectors as the dependent variable. The results in Panel A show that job creation in high-tech sectors is associated with a multiplier of around 5.2 for total employment in the low-tech industry, i.e., in both STEM and non-STEM occupations. This result is similar to the estimates in Panel B of Table 3. However, Panel B of Table 4 also presents a falsification test by showing that the multiplier for STEM occupations in low-tech sectors is much less strong, with very small estimated multipliers. Taking the evidence

Table 6. Multiplier regressions—migration

Independent variable:	OLS	IV		
		Equation (3)	Equation (4)	Equations (3) and (4)
	A. Dependent variable: Net migration			
Employment growth of (high-tech industries and STEM occupations)	0.93*	3.48*	3.19*	3.07*
	(0.18)	(0.69)	(0.67)	(0.68)
		IV first-stage coefficients		
Equation (3)	–	0.71*	–	−0.32
		(0.10)		(0.44)
Equation (4)	–	–	0.74*	1.04*
			(0.10)	(0.43)
Number of observations	*405*	*405*	*405*	*405*
IV first-stage F-statistic	–	*46.19*	*51.21*	*27.89*
IV overidentification Chi-sq statistic	–	–	–	*2.28*
	B. Dependent variable: Employment growth of non-STEM occupations in low-tech industries			
Employment growth of (high-tech industries and STEM occupations)	0.81*	3.60*	3.35*	2.66
	(0.26)	(1.14)	(1.06)	(1.07)
Employment growth of (high-tech industries and STEM occupations) × net migration	5.69	20.57	19.68	34.69
	(3.80)	(23.34)	(23.15)	(25.21)
Net migration	0.20*	−0.06	−0.04	−0.14
	(0.05)	(0.20)	(0.20)	(0.22)
Number of observations	*403*	*403*	*403*	*403*
IV first-stage F-statistic	–	*20.36*	*22.45*	*12.17*
IV overidentification Chi-sq statistic	–	–	–	*3.46*

Notes: Net migration is defined as the difference between immigration toward and emigration out of a region expressed as a percentage of the total population in that region. For Panel A, the 5-year average net migration rate is used for years 2000–2005 and 2005–2010. For Panel B, net migration in the initial period (i.e., in 2000 for the period 2000–2005 and in 2005 for 2005–2010) is used. Standard errors clustered at the regional level, and * indicates significance at the 1% level. All *F*-test statistics are significant at 1%, and the Chi-square tests statistics are not. All regressions include country-year fixed effects.

in Panels A and B of Table 4 together, these results suggest that job creation in high-tech sectors entails employment growth in low-tech sectors but only in non-STEM occupations, such unskilled workers in low-tech services.

Similarly, Table 5 estimates the local job multiplier using STEM employment growth as the independent variable, as was done in Panel C of Table 3. However, in contrast to Panel C of Table 3, Table 5 uses different dependent variables. Panel A of Table 5 uses as a dependent variable employment growth in all non-STEM occupations, both in high-tech sectors as well as low-tech sectors, whereas Panel B of Table 5 uses employment growth of non-STEM occupations only in high-tech sectors as the dependent variable. The estimated multiplier in Panel A of Table 5 is similar to estimates from Panel C in Table 3. Moreover, the falsification exercise in Panel B of Table 5 shows no evidence in support of the hyptothesis that this employment growth in non-STEM occupations is also happening in high-tech sectors. In sum, Tables 3–5 show that the local high-tech job multiplier mainly creates jobs for non-STEM unskilled workers in low-tech sectors such as local services. These results are in line with Autor and Dorn (2013) and Autor, Dorn and Hanson (2013) for the United States and Goos, Manning, and Salomons (2014) for Europe who have argued that innovation leads to growth in highly skilled occupations as well as growth in local less-skilled service employment because (i) digital technologies and highly skilled occupations are complements in local aggregate production, and (ii) innovation leads to an increase in average real income in a region, which also increases the demand for local less-skilled services that cannot easily be automated. Finally, our results suggest that regional economies are in part driven by high-tech booms (and busts), similar to literature that has examined the importance of energy boom-and-bust cycles for local labor markets—see Marchand (2012) for more details.

While the results from Tables 3–5 show that the local high-tech job multiplier results in the creation of jobs for unskilled workers in low-tech sectors, an important prerequisite for the functioning of the multiplier mechanism is

Table 7. Multiplier regressions—country groups (North-West-Center)

Independent variable:	Dependent variable: Employment growth of non-STEM occupations in low-tech industries			
	OLS	IV		
		Equation (3)	Equation (4)	Equations (3) and (4)
	A. Region: North and West (Denmark, Finland, Ireland, The Netherlands, Sweden, United Kingdom)			
Employment growth of (high-tech industries and STEM occupations)		−24.77	0.71	−0.10
		(228.09)	(2.18)	(1.33)
		IV first-stage coefficients		
Equation (3)	–	−0.05	–	−1.55
		(0.40)		(0.62)
Equation (4)	–	–	0.80	1.65*
			(0.31)	(0.44)
Number of observations	*113*	*113*	*113*	*113*
IV first-stage F-statistic	–	*0.01*	*6.65*	*7.09*
IV overidentification Chi-sq statistic	–	–	–	*0.13*
	B. Region: Central (Belgium, Denmark, France, Luxembourg)			
Employment growth of (high-tech industries and STEM occupations)	0.93*	10.16	9.21	11.01
	(0.29)	(8.87)	(9.85)	(8.72)
		IV first-stage coefficients		
Equation (3)	–	0.44	–	0.95
		(0.46)		(1.27)
Equation (4)	–	–	0.36	−0.53
			(0.43)	(1.21)
Number of observations	*124*	*124*	*124*	*124*
IV first-stage F-statistic	–	*0.92*	*0.68*	*0.55*
IV overidentification Chi-sq statistic	–	–	–	*0.06*

Notes: The dependent variable is 5-year growth of employment in the non-high-tech sector. Standard errors clustered at the regional level, and * indicates significance at the 1% level. None of the *F*-test statistics and Chi-square tests statistics is significant at the 1% level. All regressions include country-year fixed effects.

the availability of workers to fill these jobs. The increased demand for unskilled workers in low-tech sectors can be satisfied by available workers within the region, but also by attracting workers from outside the region. To see whether migration is an important channel through which the multiplier works, we can look at the link between migration and high-tech employment growth. In particular, in Panel A of Table 6 we regress the net migration rate in a region, which is the difference between immigration and emigration as a percentage of the local population, averaged over the periods 2000–2005 and 2005–2010 onto high-tech employment growth in that region between 2000–2005 and 2005–2010.[9] We find that there is indeed a positive relationship: regions with strong high-tech employment growth have higher net migration rates.

An alternative approach to test for the importance of labor mobility is to see whether the local high-tech job multiplier is higher in regions with higher net migration. Therefore, Panel B of Table 6 repeats the analysis in Panel A of Table 3, but adds an interaction effect between high-tech employment growth and the net migration rate in the initial period (i.e., in 2000 for the period 2000–2005 and in 2005 for the period 2005–2010) on the right-hand side of equation (2). In the first column using OLS, the positive coefficient on the interaction term (significant at the 15% level)

9 The net migration rate covers migration of the entire population, and hence does not focus explicitly on the working age population. However, as the majority of movers are of working age, the net migration rate is considered to be a good proxy for labor mobility (Gakova and Dijkstra, 2008).

Table 8. Multiplier regressions—country groups (South-East)

Independent variable	Dependent variable: Employment growth of non-STEM occupations in low-tech industries			
	OLS	IV		
		Equation (3)	Equation (4)	Equations (3) and (4)
	A. Region: South (Cyprus, Greece, Italy, Malta, Portugal, Spain)			
Employment growth of (high-tech industries and STEM occupations)	2.42*	5.81*	5.62*	5.23*
	(0.83)	(1.60)	(1.64)	(1.73)
		IV first-stage coefficients		
Equation (3)	–	0.59*	–	−1.31
		(0.11)		(1.26)
Equation (4)	–	–	0.61*	1.94
			(0.11)	(1.29)
Number of observations	*84*	*84*	*84*	*84*
IV first-stage F-statistic	–	*29.21*	*30.36*	*19.90*
IV overidentification Chi-sq statistic	–	–	–	*1.50*
	B. Region: East (Austria, Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Litduania, Poland, Romania, Slovakia, Slovenia)			
Employment growth of (high-tech industries and STEM occupations)	0.30	0.60	1.32	1.59
	(0.40)	(1.31)	(1.22)	(1.29)
		IV first-stage coefficients		
Equation (3)	–	0.55	–	−0.25
		(0.36)		(0.97)
Equation (4)	–	–	0.59	0.83
			(0.34)	(0.87)
Number of observations	*89*	*89*	*89*	*89*
IV first-stage F-statistic	–	*2.37*	*3.12*	*10.11*
IV overidentification Chi-sq statistic	–	–	–	*6.36*

Notes: The dependent variable is 5-year growth of employment in the non-high-tech sector. Standard errors clustered at the regional level, and * indicates significance at the 1% level. None of the *F*-test statistics and Chi-square tests statistics is significant at the 1% level. All regressions include country-year fixed effects.

suggests that the local high-tech job multiplier is larger in regions with more net migration: a 1 standard deviation increase in the net migration rate (i.e., an increase of about 5 percentage points in our data) increases the multiplier by 0.30 units.[10] The coefficients on interaction terms using IV instead of OLS are also all positive, although not statistically significant. Overall, results from Table 6 corroborate the idea that labor mobility is an important channel for the functioning of the local high-tech multiplier.

5. Regional variation in the local high-tech job multiplier

While an EU-wide estimate of the local high-tech job multiplier gives an overall sense of the impact of high-tech job creation on the demand for other jobs in a region, there could be substantial heterogeneity in the size of the local high-tech job multiplier across regions. To see whether certain groups of countries have higher local high-tech job multipliers than others, Tables 7 and 8 repeat the analysis from Panel A in Table 3 for four country groups seperately: Northern and Western Europe (Table 7 Panel A), Central Europe (Table 7 Panel B), Southern Europe (Table 8 Panel A) and Eastern Europe (Table 8 Panel B). The results show that the multipliers in the IV specifications are only significant in Southern European countries.

10 The net migration rate in the regions included in the regressions equals 2.8% on average.

Table 9. Multiplier regressions—interactions

Independent variables:	Dependent variable: Employment growth of non-STEM occupations in low-tech industries			
	OLS	IV		
		Equation (3)	Equation (4)	Equations (3) and (4)
	A. Interaction of employment growth of (high-tech industries and STEM occupations) with GDP per capita			
Employment growth of (high-tech industries and STEM occupations) × GDP per capita	−1.35*	−4.06	−4.58	−5.75*
	(0.43)	(3.87)	(2.80)	(1.97)
Employment growth of (high-tech industries and STEM occupations)	2.60*	8.96	9.32*	10.54*
	(0.54)	(3.96)	(3.27)	(3.02)
GDP per capita	0.01	0.01	0.02	0.03
	(0.01)	(0.04)	(0.03)	(0.02)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*23.24*	*23.24*	*20.47*
IV overidentification Chi-sq statistic	–	–	–	*0.46*
	B. Interaction of employment growth in high-tech industries witd share of non-STEM workers			
Employment growth in high-tech industries × share of non-STEM workers in high-tech industries	2.99	114.14	114.05	112.17
	(3.88)	(69.10)	(68.44)	(61.81)
Employment growth in high-tech industries	−1.13	−79.18	−79.12	−77.80
	(2.67)	(48.62)	(48.16)	(43.54)
Share of non-STEM workers in high-tech industries	0.07	0.17	0.17	0.17
	(0.05)	(0.13)	(0.13)	(0.14)
Number of observations	*410*	*410*	*410*	*410*
IV first-stage F-statistic	–	*5.85*	*6.05*	*3.81*
IV overidentification Chi-sq statistic	–	–	–	*0.00*

Notes: Dependent variable is employment growth of non-STEM occupations in low-tech industries. Standard errors clustered at the regional level, and * indicates significance at the 1% level. All *F*-test statistics in Panel A are significant at 1%, the *F*-test statistics from Panel B, and the Chi-square test statistics are not. All regressions include country-year fixed effects. GDP per capita is in initial period and in purchasing power parity.

To get a better understanding of these regional variations in the multiplier, we interact $\Delta H_{j,t}/E_{j,t-s}$ from equation (2) with regional gross domestic product (GDP) per capita (expressed relative to the EU-wide GDP per capita level). The results in Panel A of Table 9 show that this interaction term is significantly negative, which implies that multipliers are bigger in regions with relatively low levels of GDP per capita. One possible explanation for this finding is that high-tech employment in poorer regions is more low-skill-intensive than in richer regions,[11] and that regions that have low-skilled-intensive high-tech industries find it easier to create or fill low-skilled jobs upon the creation of high-tech jobs. To test this further, Panel B of Table 9 interacts the high-tech industry multiplier with the regional share of non-STEM employment in high-tech industries. The positive interaction term (significant at the 10% level in the IV specification) confirms that regions with more low-skilled-intensive high-tech industries have bigger high-tech multipliers. To put the point estimates from Panel B into perspective, a 1 standard deviation increase in the share of non-STEM in high-tech industries (i.e., an increase of 5.8 percentage points)[12] results in a multiplier that is 6.5 units bigger (based on the estimates from the last column).

11 The data indeed show a strong negative correlation between regional GDP per capita and the share of non-STEM in total high-tech industry employment, as well as the share of non-STEM in total employment.

12 The average share of non-STEM employment in high-tech industries for the regions included in the estimations equals 70.2%.

6. Conclusions

This study was the first to estimate an average local high-tech job multiplier across geographically dispersed labor markets in Europe. However, this article also documented that there exist important differences in the size of the local high-tech job multiplier that are persisent across regions. In particular, we find that the multiplier is larger in regions with higher immigration, an abudance of less-skilled workers, and lower gross output per capita. At the country level, we also show that this results in local high-tech job multipliers that are larger in Southern European countries than in the rest of Europe.

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Appendix

A1: Construction of the employment data set

Employment is characterised by an ISCO occupation code relating to an employee's level and field of study, and a NACE sector code relating to the employer's business activities. The definition of high-tech employment that is used throughout the main text combines employment in STEM occupations (both in high-tech and low-tech industries) and employment in non-STEM occupations in high-tech industries. Employment in high-tech industries for each NUTS-2 region is available from Eurostat's Regional Science and Technology Statistics Database that we combine with employment in STEM and non-STEM occupations aggregated from the ELFS micro data set.

We start with ELFS data from 2000 to 2007 that contains employment by two-digit ISCO occupation and two-digit industry for all EU countries. In this data set we can calculate the share of high-tech jobs that is done by STEM workers for each country and year:

$$\alpha_{c,t} = \frac{STEMhigh_{c,t}}{STEMhigh_{c,t} + nonSTEMhigh_{c,t}}.$$

This share $\alpha_{c,t}$ is then linearly extrapolated to the year 2008–2010. Note that the STEM definition used here is broader than the STEM occupations defined in the main text since we use the two-digit rather than three-digit ISCO occupations,[13] and we return to this issue below.

Multiplying high-tech employment from Eurostat with this share $\alpha_{c,t}$ gives us STEM employment in the high-tech industries for each NUTS-2 region.[14] Once we have STEM employment in the high-tech industries, we also know non-STEM employment in the high-tech industries (since we have data on total high-tech industry employment). Note that we multiply regional high-tech employment with country-level shares ($\alpha_{c,t}$), hence making the assumption that the share of STEM occupations in high-tech industry employment is the same for every region of a country.

In the most recent version of the ELFS, that has data up to 2010, we have two-digit STEM employment for every NUTS-2 region. Subtracting the just-calculated STEM employment in high-tech industries from total STEM employment taken from the ELFS gives us STEM employment in non-high-tech industries. This gives us a data set containing high-tech employment (i.e., employment in STEM occupations in high-tech and non-high-tech industries as well as in non-STEM occupations in high-tech industries), where STEM is defined at the two-digit ISCO level, from 2000 to 2010 at the NUTS-2 region.

As two-digit STEM occupations contain some occupations that should not be classified as STEM (primarily in health care), we have to adjust the STEM employment data. From the most recent ELFS data we can calculate the ratio of three-digit STEM employment to two-digit STEM employment for every NUTS-2 region and every year. We can safely assume that the two-digit STEM jobs that are not in the three-digit STEM classification are concentrated in the non-high-tech industries. Therefore, we subtract the difference between two-digit STEM and three-digit STEM for STEM employment in the non-high-tech industries and add it to non-STEM non-high-tech industry employment. This gives us a data set containing high-tech industry employment, where STEM is defined at the more restrictive three-digit ISCO level, from 2000 to 2010 at the NUTS-2 region.

Not all necessary data are present in Eurostat's Regional Science and Technology Statistics Database and the ELFS. So, we made the following adjustments:

- As we did not have data on STEM employment in high-tech industries for Romania, Poland, Bulgaria, and Malta, for the share of STEM in high-tech industry employment, we used $\alpha_{c,t}$, the average share of the new member states[15] for each year in the sample.
- The ELFS only provides two-digit ISCO employment for Bulgaria, Slovenia, and Poland. So, we made the adjustment from two-digit to three-digit STEM using the average three-digit to two-digit ratio of the new member states.
- The ratio of three-digit to two-digit STEM employment for Germany is only available from 2002, so it was linearly extrapolated to 2000 and 2001 (only at the country-level).
- The EULFS only provides one-digit ISCO employment for Malta, which makes it impossible to calculate total STEM, and therefore also STEM employment in non-high-tech industries and non-STEM employment in non-high-tech industries. To solve this issue, we assume that the share of total STEM employment in total employment equals the following:

$$STEMshare_{MT,t} = STEMshare_{EU,t} \frac{\alpha_{MT,t}}{\alpha_{EU,t}}.$$

- Germany and Austria only provide STEM employment at the NUTS-1 level. We therefore assumed that the share of total STEM employment in total employment was the same for every NUTS-2 region of a NUTS-1 region.
- The Netherlands and Denmark only provide STEM employment at the country level. We therefore assumed that the share of total STEM employment in total employment was the same for every NUTS-2 region of a country.

13 The two-digit STEM occupations are: 21, 22, 31 and 32.

14 This ELFS version only contains one-digit NACE (Nomenclature statistique des activités économiques dans la Communauté Européenne) codes and could therefore not be used for making the distinction between high-tech and non-high tech.

15 The new member states are Cyprus, Malta, Bulgaria, Romania, Poland, Czech Republic, Hungary, Estonia, Latvia, Lithuania, Slovenia, Slovak Republic.

- For 2011 we only have the Eurostat data on total employment and high-tech industry employment. To get the rest of the data, we assume that the share of total STEM employment in total employment and the share of STEM in high-tech industry employment ($\alpha_{c,t}$) are the same as in 2010.
- The final data set contains employment for our broader definition of high-tech for each NUTS-2 region in the EU for the period 2000-2011.

A2: Construction of UK employment data

For the UK we do not use the ELFS, but the country's own national labor force survey (UKLFS). This survey uses a different occupational classification, namely, the Coding of Occupations (SOC90). We classify the following occupations as STEM:

- Natural Scientists (20)
- Engineers and technologists (21)
- Architects, town planners and surveyors (26)
- Scientific technicians (30)
- Computer analysts/programmers (32)

Though not exactly the same as the STEM occupations in the ISCO classification, these occupations are very similar to the ones defined in Table 2 (STEM ISCO occupations). For the industry classification, the UKLFS uses the Standard Industrial Classification of Economic Activities (SIC92). We classify the following industries as high-tech industries:

- Manufacture of office machinery and computers (30)
- Manufacture of radio, television, and communication equipment and apparatus (32)
- Manufacture of medical, precision and optical instruments, watches and clocks (33)
- Post and telecommunications (64)
- Computer and related activities (72)
- Research and development (73)

Remark that both occupational and industry codes have been made consistent over time. As the UKLFS only provides two-digit industry codes, we cannot include the sectors "Manufacture of pharmaceuticals, medicinal chemicals and botanical products (24.4)" and "Manufacture of aircraft and spacecraft (35.3)." Therefore our UK high-tech employment data will slightly underestimate the true value.[16]

As our UKLFS data are only available until 2010, we use the growth rate of total employment from Eurostat in 2011 and to obtain values for our different employment categories in 2011.

The UKLFS only provides data at the NUTS-1 level (defined as combinations of government office regions), with the exception of London, which is divided into its NUTS-2 regions Inner London (UKI1) and Outer London (UKI2). The following steps were followed to impute high-tech employment at the NUTS-2 level:

- Using Eurostat total employment data, we calculate for each NUTS-2 region its share in total employment of the corresponding NUTS-1 region.[17] We apply this share to the total employment data of the EULFS to get total employment at the NUTS-2 level.
- To get total employment in high-tech industries we apply the same method to Eurostat high-tech employment data.[18]

16 Estimations show that the inclusion of the sectors "Manufacture of pharmaceuticals, medicinal chemicals and botanical products (24.4)" and "Manufacture of aircraft and spacecraft (35.3)" would have only increased UK high-tech employment by 0.9% in 2007. Their exclusion will hence have a negligible impact on the UK data.

17 The total employment data differ only slightly between the European and the UK labour force.

18 Although the high-tech employment data from the European LFS and the UK LFS show substantial differences, the distribution of high-tech employment over the NUTS-1 regions is very similar. We therefore assume that the distribution over the NUTS-2 regions will also be reliable.

- For STEM employment at the NUTS-2 level, we assume that the STEM share of total employment is the same for every NUTS-2 region of a NUTS-1 region.
- After applying the share of STEM in high-tech ($\alpha_{c,t}$) to total high-tech at the NUTS-2 level, we can calculate employment for all different categories.

The final data set contains employment for our broader definition of high-tech for each NUTS-2 region in the UK for the period 2000–2011.