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Abstract

This paper shows that high-tech employment – broadly defined as all workers in high-tech sectors but also workers with STEM degrees in low-tech sectors- has increased in Europe over the past decade. Moreover, we estimate that every high-tech job in a region creates five additional low-tech jobs in that region because of the existence of a local high-tech job multiplier. The paper also shows how the presence of a local high-tech job multiplier results in convergence is happening at a glacial pace, and some suggestive evidence is presented that lifting several institutional barriers to innovation in Europe's lagging regions would speed up convergence leading to faster high-tech as well as overall employment while also addressing Europe's regional inequalities.

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1 Introduction

Europe’s Innovation-Union initiative aims to create an innovation-friendly environment to bring economic growth and jobs to its regions. For example, it strives for a 50% (or 150 billion Euro) increase in R&D investments by 2020, claiming this could increase employment by 1.7% (or by 3.7 million jobs) by 2025. Moreover, the Innovation-Union plan contains over thirty action points to guarantee that this growth is inclusive with more and better jobs for all. In line with these objectives, this paper shows that R&D investments in Europe have created jobs over the past 15 years indeed. Moreover, the paper shows that especially employment in Europe’s lagging regions has benefited from innovation, leading to their convergence towards Europe’s prosperous high-tech hubs and, hence, to inclusive job growth. However, in contrast to the Innovation-Union objectives, this paper also shows that this convergence is happening at a glacial pace: it will take at least 60 years for Europe’s lagging regions to close half of their current lack of high-tech employment compared to Europe’s high-tech hubs. Finally, this paper conjectures that this slow speed of convergence is, in part, due to several obstacles to innovation in Europe’s lagging regions that prevent the rapid accumulation of physical, human and social capital.

Figure 1 shows the cumulative percentage growth in high-tech and total employment in the EU27 between 2000 and 2011.² As shown in the figure, high-tech has been an important source of total employment growth during this period. Between 2000 and 2011, high-tech employment in the European Union grew by a cumulative 19%, compared to a total employment growth of 8%.³ While high-tech employment growth clearly outpaced total employment growth in this eleven-year period, Figure 1 also shows that there are three years in which it was relatively slow. A first episode was 2001-2002 after the collapse of the high-tech bubble. A second episode was during the year 2010, characterized by a decrease in aggregate demand for manufactured goods including high-tech exports. In sum, barring short-run cyclical downswings, high-tech employment growth is an important driver of overall employment growth in Europe.

Whereas Figure 1 pools all 27 EU countries, the vertical axis of Figure 2 shows that there also exist large differences between countries in high-tech employment growth. In particular, Figure 2 shows that a country’s growth in high-tech employment between 2000 and 2011 is negatively correlated with its initial share of high-tech employment in 2000. That is, countries with relatively low initial shares of high-tech employment had stronger high-tech job growth in the subsequent 11-year period. For example, in 2000 the share of high-tech jobs in total Spanish employment was 6% compared to 12% in Germany. Between 2000 and 2011, high-tech employment increased

²The European Union refers to 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 Appendix A.

³Goos et al. (2013) further documents this increasing trend in high-tech jobs for separate European countries.

by a rapid 51% in Spain compared to 13% in Germany. The downward sloping regression line in Figure 2 suggests that this convergence of Europe’s lagging countries towards Europe’s high-tech champions exists more generally in the data. Below we show that this convergence also exists between 227 more narrowly defined NUTS-2 regions in Europe for which we have data.⁴

The first contribution of this paper is to explain Europe’s long-run rise in high-tech and overall employment (as indicated by Figure 1) and it’s convergence between regions (as indicated by Figure 2) by introducing a local high-tech job multiplier into a standard growth framework. In this framework, innovation increases the demand for high-tech workers in a region. In turn, these high-tech workers generate other jobs in that region, resulting in a local high-tech job multiplier denoted by γ and that we estimate to be around 5. That is, every high-tech job in a region creates five other jobs in that region. In particular, high-tech workers demand services that can only be provided locally, such as household services, healthcare, childcare, restaurants, schools, shops, transport, or sporting and cultural activities. The existence of a local high-tech job multiplier leads to growth in high-tech but also overall employment, as Figure 1 indicates. Moreover, the local high-tech job multiplier implies that the share of high-tech in total employment must increase towards $1/(1+\gamma) = 1/(1+5) = 17\%$ in each region in the long-run, and that this increase is faster the lower is a region’s initial high-tech employment share.⁵ Our estimates below provide evidence for this convergence between regions in their high-tech employment shares, as Figure 2 suggests.⁶

However, our estimates will also show that this convergence is happening at a glacial pace: it will take Europe’s lagging regions at least 60 years only to close half their gap with Europe’s high-tech hubs. For example, in 2011 18% of Stockholm’s 1.1 million workforce was employed in high-tech jobs.⁷ In contrast to this, only 4% of the 1.1 million workers in the Centro region of Portugal are in high-tech jobs. What this paper will show is that the Centro region in Portugal

⁴The NUTS classification (Nomenclature of territorial units for statistics) is used to divide the European territory into regions of different population sizes (NUTS-1, NUTS-2 and NUTS-3). The NUTS-2 regions are the basic regions for the application EU regional policies.

⁵To see that this is the case, denote high-tech employment in a region at time t by $H(t)$ and other employment by $L(t)$. Also assume that initial employment in a region is given by \bar{L} and that the local high-tech job multiplier is 5, such that $L(t) = 5H(t) + \bar{L}$ and the share of high-tech in total employment is $s(t) = H(t)/(6H(t) + \bar{L})$. Taking the limit for $t \rightarrow \infty$ of $s(t)$ gives $1/6 = 17\%$. Moreover, the growth rate in $s(t)$ is given by $g_s = (1 - 6H(t)/(6H(t) + \bar{L}))g_H$ with g_H the growth rate in high-tech employment. For given g_H , we get that g_s is larger the larger is \bar{L} and thus the smaller is $s(t)$, i.e. there is convergence.

⁶Strictly speaking, the vertical axis of Figure 2 plots the growth rate of the level of high-tech employment whereas the convergence equations estimated below use the growth rate in the *share* of high-tech employment as the dependent variable instead. To see that this does not matter, we know from the previous footnote that the growth rate in the share of high-tech employment is given by $g_s = (1 - 6H(t)/(6H(t) + \bar{L}))g_H$. So if innovation leads to higher g_H if \bar{L} is larger and thus $s(t)$ is smaller, as Figure 2 suggests, it must also be the case that g_s is larger.

⁷Perhaps Stockholm is best known for Ericsson’s headquarters, but it is also home to several other tech-companies such as Microsoft, Intel and IBM.

is looking increasingly like Stockholm, but that this convergence is extremely slow: it will take at least until 2070 to increase the share of high-tech employment in the Centro region of Portugal to 11% (4% plus half of the difference between Stockholm's 18% and Centro's 4% today).

The second contribution of this paper is to explain why convergence is so slow. In particular, we show that Europe's lagging regions are characterized by several obstacles to innovation that hamper the fast accumulation of physical, human and social capital. Physical capital accumulation in Europe's lagging regions is hindered by a restricted role for public investment in R&D that serves as a catalyst for innovation in a region through, for example, public-private-partnerships. Also, the ease of access to finance as reported by firms is lower in Europe's lagging regions, suggesting the need for policies that inform creditors about investment opportunities and that provide forms of insurance against investment risk. Convergence of Europe's lagging regions is also slowed by several factors preventing the fast accumulation of human capital. Limited and ineffective public investments in tertiary education and in R&D spending in higher education more particularly are restricting the supply of high-tech skills necessary to create jobs. Finally, the paper also shows that institutions are less favorable for the accumulation of social capital. We show that active participation in voluntary organizations – a measure of bridging social capital to capture a region's networking abilities – is lower in Europe's lagging regions. Moreover, these regions generally have lower trust in institutions (broadly defined including the police, social security, health care, the justice system).

This paper contributes to several existing literatures examining related questions. For US cities, the importance of high-tech job multipliers is shown by Moretti (2010): while the multiplier for employment in sectors producing non-tradeables from job creation in sectors producing tradables is shown to be around 1.5, the multiplier from job creation in sectors producing innovative tradeables is estimated to be around 5. Moretti and Wilson (2014) find a large local job multiplier, especially for construction and retail, from job creation in biotech companies in the US. For Swedish and US metropolitan areas, Moretti and Thulin (2013) confirm the existence of a local high-tech job multiplier. According to Moretti (2012), the local high-tech job multiplier can be explained by (i) innovation leading to high-tech job growth and growth in local services because innovation and jobs are complements in local aggregate production – a supply-side channel – and (ii) an increase in consumer demand for high-tech goods and local services because their relative price falls following innovation or because their demand is relatively income elastic and real income increases – a demand-side channel. We return to the importance of both these channels in our discussion below.

Our analysis of regional convergence in high-tech employment shares relates to a literature estimating convergence equations. Rodrik (2013) shows for a large set of developed and develop-

ing countries that labor productivity in manufacturing is converging. Sondermann (2014) tests for convergence of labor productivity among eurozone countries. He finds that convergence does not exist between countries' average labor productivity, but that it does exist for selected sectors: "transport and communication"; "financial intermediation"; "chemicals and fuels"; "paper, printing and publishing"; and "other manufacturing". Although these sectors partially overlap with our definition of high-tech as will become clear below, an important difference is that we do not look at convergence in labor productivity but in high-tech employment shares rooted in the existence of a local high-tech job multiplier.

Finally, our analysis of why regional convergence is so slow relates to existing work examining regional differences in economic outcomes in the long-run. Filippetti and Peyrache (2015) argue that European regions have different capacities to adopt new technologies leading to long-lasting differences in labor productivity growth. To explain this, Filippette and Peyrache (2015) point to impediments to adopt more productive technologies in Europe's lagging regions, and the need for investment in physical and human capital in those regions. In this paper we also look at policies that could accelerate physical and human capital accumulation in Europe's lagging regions, but with a focus on faster convergence in high-tech employment shares rather than in labor productivity. Moreover, we show that social capital also is an important factor in explaining slow convergence, building on work by Audretsch et al (2012), Audretsch and Keilbach (2004), Miguelez, Moreno and Artis (2011), Akçomak and ter Weel (2009), and Hauser, Tappeiner and Walde (2007).

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 uses these data to (i) test for the existence of a local high-tech job multiplier; (ii) test for convergence in high-tech employment shares between European regions; and (iii) provide some suggestive evidence for why convergence is so slow. Section 4 concludes.

2 Data

We begin by defining high-tech employment as all workers employed in high-tech industries listed in Panel A of Table 1. These high-tech industries follow Eurostat's definition based on a firm's NACE code and include high-tech manufacturing (e.g. the production of robots or airplanes) as well as high-tech knowledge-intensive services (e.g. ICT consulting or the scientific research and development of new technologies). Manufacturing sectors are labeled 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 on its share of tertiary educated persons. Employment in high-tech industries for each NUTS-2 region is available from Eurostat's Regional Science and Technology Statistics Database.

To get total high-tech employment, we add to employment in these high-tech industries all workers engaged in highly technical activities in non-high-tech industries. In particular, we add to all workers employed in high-tech industries all those in Science, Technology, Engineering, and Math (STEM) occupations employed in industries 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 - see Hecker (2005). 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 set⁸, and merged at the NUTS-2 level with the data for the high-tech industries from Panel A of Table 1.⁹

Figure 3 shows 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 industries, growing by a cumulative 37% between 2000 and 2011. Also workers with STEM degrees not employed in high-tech industries 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 the traditional high-tech industries as STEM employment has been the main driver of total high-tech employment growth.

The faster growth of high-tech than total employment documented in Figure 3 implies that the share of high-tech in total employment must increase over time: the share of high-tech employment in European total employment increased from 9% in 2000 to 10% in 2011. However, large differences in the share of high-tech employment remain between NUTS-2 regions in Europe as can be seen in Figure 4. 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 of sufficiently large size, i.e. with an employed population of at least one million, in terms of high-tech intensity in 2011. The top regions include large capital regions, such as Paris, London, Berlin and Stockholm, as well as regions with a strong sectoral specialisation, such as Midi-Pyrénées (aerospace, ICT and agro-food) and Stuttgart (mechanical engineering). The lagging regions are mainly located in Southern European countries and Romania.

⁸For the UK we use the UK Labour Force Survey rather than the ELFS.

⁹Details on the construction of the high-tech employment dataset can be found in Appendix A.

3 Empirical analysis

Using the high-tech data described above, this section first estimates the presence and size of the local high-tech job multiplier in sub-section 3.1, by correlating changes in high-tech employment to changes in employment outside the high-tech sector in the same region. As the existence of a local multiplier implies a steady-state high-tech employment share, the second sub-section 3.2 looks at convergence in high-tech employment between European regions. Finally, some suggestive evidence for factors hindering convergence is given, with a focus on physical, human and social capital in sub-section 3.3.

3.1 Estimating the local high-tech job multiplier

Moretti (2010) shows for US cities that job creation in the tradeable manufacturing sector leads to additional employment in the nontradable sector in the same city. This multiplier is found to be significantly stronger when focusing on the multiplier effect from job creation in tradeable manufacturing sectors that are more innovative, such as the high-tech sector (Moretti, 2010) or the biotech sector (Moretti and Wilson, 2014). Qualitatively similar evidence for a local high-tech job multiplier was found for Swedish and US metropolitan areas by Moretti and Thulin (2013).

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

$$\Delta L_{j,t} = \gamma \Delta H_{j,t} \quad (1)$$

with $\Delta L_{j,t}$ the absolute change in non-high-tech employment in NUTS-2 region j between periods t and $t - s$ and $\Delta H_{j,t}$ the absolute change in high-tech employment. Adding a country-time fixed effect, $F_{c,t}$, to control for changes in non-high-tech employment between period t and $t - s$ that are common across all regions j in the same country c and an error term $v_{j,t}$, we get:

$$\Delta L_{j,t} = \gamma \Delta H_{j,t} + F_{c,t} + v_{j,t} \quad (2)$$

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 and non-high-tech employment. To address this issue, we follow Moretti (2010) in constructing Instrumental Variables (IV). Intuitively, the instruments are counterfactual changes in high-tech employment that capture exogenous changes in local labor demand that do not reflect local economic conditions.

A first instrument is given by:

$$\Delta \hat{H}_{j,t}^1 = H_{j,t-s} [\ln(H_{c,t} - H_{j,t}) - \ln(H_{c,t-s} - H_{j,t-s})] \quad (3)$$

where the last term in square brackets is, by approximation, average growth in high-tech em-

ployment in country c excluding region j . This average growth rate – which is region specific – is multiplied by region j 's initial level of high-tech employment to get $\Delta\widehat{H}_{j,t}^1$. This is a valid instrument if it is asymptotically correlated to $\Delta H_{j,t}$ but not to $v_{j,t}$.

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

$$\Delta\widehat{H}_{j,t}^2 = \sum_{i \in H} H_{i,j,t-s} [\ln(H_{i,c,t} - H_{i,j,t}) - \ln(H_{i,c,t-s} - H_{i,j,t-s})] \quad (4)$$

where the different components i are STEM in high-tech, STEM in non-high-tech and non-STEM in high-tech. 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 5-year differences¹⁰, with both OLS and IV. The IV analysis is done for each instrument separately, as well as for both instruments jointly. As a robustness check, the last two columns of Table 3 also report the results for STEM workers only, as Figure 3 has shown that STEM employment is the most important driver of high-tech and total employment growth. Turning to the point estimates, OLS suggests that the creation of one high-tech job leads to about 2.5 other jobs in the same region. The IV specifications lead to significantly higher coefficients: irrespective of the instrument used, the results indicate that each additional high-tech job results in 4.75 other jobs in the same region.¹¹ The OLS and IV results for the STEM multiplier in the last two columns of Table 3 provide similar insights.

Two additional conclusions can be drawn from Table 3. Firstly, the higher IV than OLS estimates suggest that $\Delta H_{j,t}$ is negatively correlated with $v_{j,t}$ in equation (2). This could be the case if, for example, the creation of high-tech jobs in a region is increasing house prices in that region. Consequently, some other workers in lower-paid jobs such as cleaners, care takers, waiters, teachers, shop assistants or drivers find that region less attractive, thereby resulting in a downward biased estimate of the local high-tech job multiplier when using OLS but not IV when estimating equation (2). Secondly, our estimates for the local high-tech job multiplier are in the upper-range of estimates found in Moretti (2010) and Moretti and Wilson (2014) for the US and Moretti and Thulin (2013) for Sweden and the US. One reason why we find relatively large estimates is that those papers look at multiplier effects from job creation in sectors producing tradeables, only some of which are high-tech. Moreover, as Figure 3 has shown, innovation also directly leads to growth of STEM employment in non-tradeable sectors, and the last two columns of Table 3 show that accounting for this is also important.

¹⁰The results are robust to different growth periods.

¹¹The specification that uses both instruments allows us to test for the validity of the instruments. According to the Sargan test, which has a p-value of 0.673, our instruments are valid.

The local high-tech job multiplier can work through various channels. According to Moretti (2012), the local high-tech job multiplier can be explained by (i) innovation leading to high-tech job growth and growth in local services because innovation and jobs are complements in local aggregate production – a supply-side channel – and (ii) an increase in consumer demand for high-tech goods and local services because their relative price falls following innovation or because their demand is relatively income elastic and real income increases – a demand-side channel. This is in line with Goos, Manning and Salomons (2014) who find that ongoing technological progress leads to job polarization in Europe. Employment is polarizing into high-paid jobs, many of which are in our definition of high-tech, and low-paid jobs mainly in local services, at the expense of middling-paid jobs such as office clerks and machine operators. Moreover, they find that job polarization exists both within-industries as well as between-industries. In their framework, innovation leads to within-industry job polarization because digital capital easily substitutes for routine middling-paid jobs but not for non-routine high-paid and low-paid jobs in aggregate production. For example, investments in computers have decreased demand for middling-paid office clerks but have increased demand for high-paid professional technicians as well as low-paid security personnel within many industries. But Goos, Manning and Salomons (2014) also find an important between-industry component to job polarization that works through changes in relative output prices and an increase in real income. In particular, innovation leads to a fall in the output price of high-tech goods which increases the demand for high-tech products and therefore high-tech jobs. Moreover, a fall in the output price of high-tech goods increases real income in a region. Consequently, the demand for low-paid local services such as household services, healthcare, childcare, restaurants, schools, shops, transport, or sporting and cultural activities increases too. Similar evidence in line with the existence of a local high-tech job multiplier is found in Autor and Dorn (2013) and Autor, Dorn and Hanson (2013) for the US.

3.2 Estimating convergence in high-tech employment shares

The existence of a local high-tech job multiplier implies that the share of high-tech workers in total employment in region j at time t , $s_{j,t} = H_{j,t}/(H_{j,t} + L_{j,t})$, converges to $s^* = 1/(1 + \gamma)$. For example, a multiplier of $\gamma = 5$ implies that every high-tech job creates five other jobs, such that the share of high-tech workers in total employment will be $s^* = 1/(1 + 5) = 17\%$ in the steady state. In the short run, $s_{j,t}$ will increase if $s_{j,t} < s^*$, i.e. the regional shares $s_{j,t}$ will converge to the steady-state share s^* .¹² To illustrate this, Figure 5 simulates the evolution of the high-tech employment share assuming that $s_{j,0} = 7\%$ and $\gamma = 4.75$. The figure shows that the high-tech job

¹²Note that it is also true that $s_{j,t}$ will decrease if $s_{j,t} > s^*$. However, we do not explicitly discuss this possibility here as it is irrelevant for the large majority of regions in our sample.

multiplier results in an increase in the high-tech employment share over time. It also shows that this increase is decreasing with time, i.e. there is convergence. Finally note how these convergence dynamics are rooted in the existence of a local high-tech job multiplier.

To see this more formally, start with the following partial adjustment expression for $s_{j,t}$ depending on its share in the previous period, $s_{j,t-1}$, and on its steady-state value, $s^* = 1/(1 + \gamma)$ ¹³:

$$\ln s_{j,t} = [1 - \lambda] \ln s_{j,t-1} + \lambda \ln s^* \quad (5)$$

where $0 < \lambda < 1$ captures the speed of convergence towards steady state. If λ is large, the share of high-tech employment in a region converges faster to its steady state value s^* for any given $s_{j,t-1}$.

For a given high-tech employment share in an initial period $t = \tilde{t}$, $s_{j,\tilde{t}}$, the solution to the difference equation (5) is given by:

$$g_{s_{j,T}} = [1 - [1 - \lambda]^T][\ln s^* - \ln s_{j,\tilde{t}}] \quad (6)$$

with $T \equiv t - \tilde{t}$ and $g_{s_{j,T}} \equiv \ln s_{j,t} - \ln s_{j,\tilde{t}}$ an approximation of the growth rate of the high-tech employment share in region j between periods \tilde{t} and t . Note that because $[1 - [1 - \lambda]^T] > 0$, we must have that $g_{s_{j,T}} > 0$ if $\ln s_{j,\tilde{t}} < \ln s^*$. That is, if the share of high-tech employment is initially below its steady-state value, it must increase over time. Also note that $g_{s_{j,T}}$ is larger the larger is $\ln s^* - \ln s_{j,\tilde{t}}$, i.e. there is convergence.

Empirically, the convergence equation (6) can be estimated as:

$$g_{s_{j,T}} = \beta_0 + \beta_1 \ln s_{j,\tilde{t}} + F_T + \varepsilon_{j,T} \quad (7)$$

with $\beta_0 \equiv [1 - [1 - \lambda]^T] \ln s^*$ and $\beta_1 \equiv -[1 - [1 - \lambda]^T]$, where F_T controls for changes between periods \tilde{t} and t in high-tech employment shares that are common across regions, and with $\varepsilon_{j,T}$ an error term. Note that $\beta_1 < 0$ if convergence exists in our data. Rey and Montouri (1999) and Dall'erba and Le Gallo (2006) argue that it is important to test for spatial interdependence when looking at regional convergence. To this end, a spatial lag of employment growth can be added to the right-hand side of equation (7) but this did not change our results so we do not include it in the discussion here.

The first column in Table 4 tests for convergence between NUTS-2 regions assuming $T = 1$ such that $\beta_1 \equiv -\lambda$. The point estimate for β_1 of -1% is negative and significant, consistent with the hypothesis that there is convergence in high-tech employment shares across NUTS-2 regions in Europe. However, $\lambda = 1\%$ also implies that the speed of convergence is very slow. One way to see this is to compute the time it would take for a region with $s_{j,\tilde{t}} < s^*$ to close half the gap

¹³See Barro and Sala-i-Martin (1992) for details.

between $\ln s_{j,\tilde{t}}$ and $\ln s^*$. To do so, write equation (6) as:

$$\ln s_{j,t} - \ln s_{j,\tilde{t}} = [1 - [1 - \lambda]^T][\ln s^* - \ln s_{j,\tilde{t}}] \quad (8)$$

such that for $\ln s_{j,t} - \ln s_{j,\tilde{t}} = 0.5[\ln s^* - \ln s_{j,\tilde{t}}]$ we must have that $0.5 = 1 - [1 - \lambda]^T$ or $T = \ln(0.5)/\ln(1 - \lambda)$. Given an estimate for λ of 1%, we get that $T = 63$ or that it will take almost 63 years for a region to close half of today's gap with its steady-state level. This estimate for λ , the speed of convergence, as well as the estimated time-to-half are added at the bottom of the first column in Table 4.

The remaining columns in Table 4 check the robustness of our results. The second column extends the growth period to 5 years, i.e. $T = 5$, to find an estimate for $\beta_1 \equiv -[1 - [1 - \lambda]^5]$ of -4% . When extending the time period to $T = 10$, we get an estimated β_1 of -8% . Both estimates are negative and statistically significant, consistent with the existence of convergence across NUTS-2 regions in Europe. Again, as indicated at the bottom of Table 4, the estimated time-to-half for $T = 5$ equals 77 years and for $T = 10$ equals 88 years, suggesting very slow convergence. Similar evidence is found in the last three columns of Table 4 using more aggregate NUTS-1 regions instead.

To further illustrate the result that convergence is slow, Figure 6 shows the relationship between the share of high-tech employment in 2000 and in 2011 for different groups of NUTS-2 regions. In 2000, the regions with the lowest initial shares were mainly located in Southern European countries, while the leading regions are concentrated in Northern and Western Europe. The figure clearly shows the presence of convergence, with regions with low initial high-tech employment shares having stronger high-tech employment growth. However, the figure also shows that even in 2011 there remain significant gaps between Europe's lagging regions and its high-tech hubs. This illustrates that the speed of convergence is slow.

3.3 Why is convergence so slow?

As the speed of convergence is found to be slow, large disparities between the regions will sustain for decades if policies remain unchanged. In this section we try to shed some light on the possible causes of this low speed of convergence by focussing on the roles of different institutions. While there are many possible explanations for regional differences and identification of causal relationships is difficult, in this section we provide some suggestive evidence for the roles of (i) physical capital through public investment in R&D and access to bank loans, (ii) human capital, and (iii) social capital.

3.3.1 Public investment in R&D and access to bank loans

Governments can stimulate innovation by investing in R&D activities. This will not only directly impact employment in the R&D sector, it can also crowd-in private sector R&D expenditure (Guellec and Van Pottelsberghe De la Potterie, 2003; Almus and Czarnitzki, 2003).¹⁴ Panel A of Figure 7 plots a country's high-tech employment share in 2011 against government expenditure on R&D as a share of GDP in 2011. This measure captures investments in research units in the government sector that are outside universities, as investment in universities will be discussed separately in the next sub-section. In 2011, government expenditure on R&D ranged from almost 0% of GDP in Malta to 0.4% of GDP in Germany. High-tech employment shares in 2011 ranged from 6% in Portugal to 14% in the Czech Republic. The added regression line suggests a positive correlation between a country's high-tech employment share and government expenditure on R&D as a share of GDP. Moreover, the figure suggests that governments in Europe's lagging countries are spending their R&D budgets less effectively, and that this could be important. For example, assume for simplicity that only government spending on R&D matters for high-tech employment. The figure then shows that, if the Greek government would spend its 0.17% of GDP on R&D as effectively as Belgium, its employment share would increase from 6% to 12%. Panel B of Figure 7 provides similar evidence across NUTS-2 regions for which we have data. In sum, higher and more effective R&D spending by governments in Europe's lagging regions could speed up their convergence.

A second measure related to physical capital accumulation and the speed of convergence is access to loans to invest in innovative activities. Figure 8 uses the OECD Science, Technology and Industry database to derive a measure of "ease of access to loans" as reported by firms in 2007.¹⁵ The figure shows a positive correlation between a country's high-tech employment share and its access to loans as reported by firms. What this positive correlation suggests is that restricted access to loanable funds hampers high-tech investment and therefore the creation of high-tech jobs in Europe's lagging regions. This is in line with Colombo and Grilli (2007) who show that it is particularly difficult for high-tech start-ups to get access to bank loans. Reasons for this could be the higher ex-ante uncertainty about the successfulness of investment projects due to a lack of information or the presence of knowledge externalities characterizing high-tech hubs.

In sum, government spending on R&D and its effectiveness in creating jobs as well as the allocation of investment funds through financial markets are relatively low in Europe's lagging regions, leading to a slowdown in their convergence. Therefore, spending a larger share of public

¹⁴While there is a large body of literature that finds positive effects of R&D expenditure on business R&D activities, there is also evidence of crowding out effect. See David, Hall and Toole (2000) for a systematic review.

¹⁵The conclusions do not change when using the share of firms reporting pressing problems of access to finance from the European Commission's Survey on the Access to Finance of Enterprises.

funds on R&D more effectively in Europe’s lagging regions as well as better management of financial flows towards those regions – mainly through the provision of information to creditors about investment opportunities and through forms of insurance against investment risks – seem viable policy options that would speed up convergence and overall job growth in Europe.

3.3.2 Human capital

Panel A of Figure 9 plots, on its horizontal axis, the relationship between a country’s expenditure on R&D in higher education as a share of GDP in 2011. This includes, for example, researchers employed in academic research centers that are not exclusively in STEM fields.¹⁶ The figure shows a clear positive relationship between spending on R&D in higher education and a country’s high-tech employment share. Moreover, the figure suggests that in some countries expenditure on R&D in higher education seems to create fewer high-tech jobs than in other countries. To see this, assume for simplicity the absence of determinants directly affecting high-tech employment other than expenditure on R&D in higher education. Portugal and Germany both spend 0.5% of their income on R&D in higher education but their high-tech employment shares are 6% and 12% respectively, suggesting that the Portuguese government could double its high-tech employment share by spending its investment on R&D in higher education more effectively. The same conclusions can be drawn from Panel B of Figure 9, showing a similar correlation between a NUTS-2 regions for which we have data. In sum, the quantity and quality of expenditure on R&D in higher education is an important catalyst for human capital accumulation, and a lack thereof in Europe’s lagging regions contributes towards their slow speed of convergence.

Panel A of Figure 10 uses, on the horizontal axis, the share of tertiary educated aged 25-64 in a country in 2011. Although still positive, the correlation with a country’s high-tech employment share is weak.¹⁷ One reason for this is that part of tertiary education is less strongly related to R&D in higher education and to STEM fields. For example, the share of tertiary educated in both Spain and The Netherlands was 32% in 2011. However, the high-tech employment shares are 7% and 10% respectively. What this suggests is that, all else equal, tertiary education in Spain is less efficient in leading to high-tech jobs which is slowing Spain’s convergence towards Europe’s high-tech hubs. This finding is in line with Hanushek and Woessmann (2015) who show that not only the quantity but also the quality of high-skilled workers is important for economic growth. Another reason for the weak correlation found in Panel A of Figure 10 could be because there is substantial

¹⁶Expenditure on R&D in higher-education, such as university research centers, was not included in the definition of government spending on R&D discussed in the previous sub-section.

¹⁷The correlation is significantly stronger when using the share of adults with high literacy proficiency levels (defined as having at least PIAAC literacy level 3, see OECD (2013)). This definition of human capital is argued to be preferred over the share of tertiary educated adults as its international comparability is higher. The data are, however, only available for 17 EU countries.

variation in tertiary educational attainment rates between regions within a country. Therefore, Panel B of Figure 10 uses the NUTS-2 regional share of the tertiary educated population aged 25-64 in 2011 and plots this against our NUTS-2 estimates of high-tech employment shares for which we have data. The figure shows a strong positive correlation, with especially investments in tertiary education in the Eastern and Southern regions low and ineffective in creating high-tech jobs.

In sum, the fast accumulation of human capital to speed up convergence in Europe's lagging regions is hampered by low public investment in higher education. Moreover, an increase in government spending on tertiary education in general and R&D in higher education in particular needs to become more effective in creating high-tech and other jobs.

3.3.3 Social capital

Whereas the relationship between economic activity and physical and human capital has been analysed extensively, the importance of social capital for innovation is much less researched. The concept of social capital was developed by Bourdieu (1986), Coleman (1988) and Putnam (1993), and generally refers to "the networks together with shared norms, values and understandings that facilitate co-operation within or among group" (OECD, 2001). Existing evidence (Putnam, 1993; Knack and Keefer, 1997) suggests that social capital has contributed to economic performance of countries and regions, but the channels through which this happens such as the role of innovation remain largely unknown and this sub-section sheds some light on this.

Measuring social capital is not straightforward. van Oorschot, Arts and Gelissen (2006) develop a framework of eight indicators of social capital. Of those eight indicators, we retain two that have been shown to be related to innovation: "participation in voluntary organizations" and "trust in institutions". For example, Miguelez, Moreno and Artis (2011) argue that social networks enable individuals to share knowledge, with is conducive to innovation. Also, trust in institutions is beneficial for entrepreneurship as it makes individuals, including investors, less risk-averse. Their results show that social capital has been important for innovation in Spanish regions. The importance of local entrepreneurship capital has also been stressed by Audretsch et al. (2012) and Audretsch and Keilbach (2004). Similarly, Hauser, Tappeiner and Walde (2007) test the relationship between regional innovative capacity and different elements of social capital and find that only associational activity is strongly connected to innovation. A positive effect of trust in others on innovation and therefore also on income growth was found by Akçomak and ter Weel (2009) for European Union countries.

Figure 11 shows the relationship between high-tech employment shares and active participation in voluntary organizations in 2000 for our sample of countries. Both measures are positively correlated. Moreover, in some countries networking opportunities are not used as efficiently as

in other countries. Greece, for example, has the same level of active participation in voluntary organizations as the Netherlands, but its high-tech employment share is much lower, implying that the social networks in Greece are not optimally used.

The correlation between high-tech employment shares and trust in institutions is shown in Figure 12.¹⁸ Countries with low levels of trust have lower high-tech employment shares, confirming that trust is indeed important for innovation. Again some countries appear to use their social capital inefficiently, as they combine high levels of social capital with low levels of high-tech intensity. An example is Spain, which has a similar level of trust as Germany, Belgium and France, but a much lower share of high-tech employment.

We can conclude from Figures 11 and 12 that low levels of social capital can hinder convergence between the European regions or countries. Better social networks and increased trust in institutions could potentially lead to more innovation, which would fasten the growth of high-tech employment in the lagging regions.

4 Conclusions

At least over the past decade, innovation has led to strong high-tech employment in Europe. Moreover, the existence of a local high-tech job multiplier implies that each of these high-tech jobs demands other low-tech jobs in the same region, leading to Europe's prosperous high-tech hubs. Also, the existence of a local high-tech job multiplier implies that the share of high-tech in total employment in a region must increase to a steady-state share (of 17% in case the local high-tech job multiplier is five) in the long-run, and that this increase is faster in regions that have lower initial high-tech employment shares. That is, employment in Europe's lagging regions is becoming more similar to Europe's high-tech hubs. In sum, innovation is leading to strong high-tech and overall employment growth while, in principle, also addressing Europe's regional inequalities.

However, it was also shown that the speed at which Europe's lagging regions are becoming more similar to Europe's high-tech hubs is very slow: it will take at least 60 years to close half of the current gap between Europe's lagging regions and its high-tech hubs. We argued that this is due to several institutional obstacles related to innovation that exist in Europe's lagging regions. Consequently, appropriate policies targeted towards Europe's lagging regions could mitigate the impact of these obstacles. These policies are (i) an increased involvement of public investment in R&D through public-private-partnerships; (ii) easier access for innovating firms to financial market funds by reducing uncertainty and providing risk insurance for creditors; (iii) increased and more effective spending on tertiary education in general and R&D in higher education in particular; and

¹⁸Institutions consists of all (welfare) state institutions, i.e. the police, the social security system, the health care system, parliament, the civil service and the justice system. The conclusions are robust to using trust in national government from the 2011 Eurobarometer (Spring edition).

(iv) networking initiatives for sharing information within and between different regions in Europe. Targeting these policies towards Europe's lagging regions would lead to faster convergence and stronger high-tech and overall job growth while, in practice, also addressing Europe's regional inequalities.

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Appendix A

A1: Construction of the employment dataset

Employment is characterized 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 European Union Labour Force Survey (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 dataset 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 occupations¹⁹, 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 region²⁰. 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 dataset containing high-tech employment (that is, 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

¹⁹The two-digit STEM occupations are: 21, 22, 31 and 32.

²⁰This ELFS version only contains one-digit NACE codes and could therefore not be used for making the distinction between high-tech and non-high tech.

STEM (primarily in healthcare), 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 dataset 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 states²¹ 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.

²¹The new member states are CY, MT, BG, RO, PL, CZ, HU, EE, LV, LT, SI, SK.

- 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.
- For 2011 we only have the Eurostat data on total employment and high-tech industry employment. In order 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 dataset 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 United Kingdom employment data

For the United Kingdom we do not use the ELFS, but the country's own national labour 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 value²².

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 region²³. 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.²⁴
- 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.

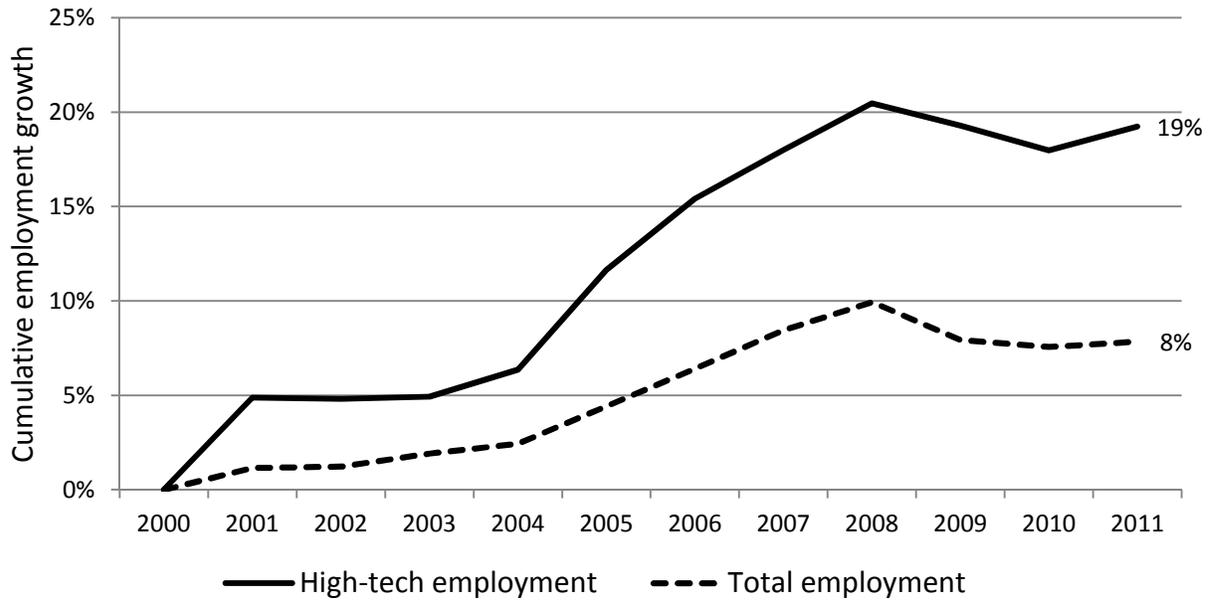
The final dataset contains employment for our broader definition of high-tech for each NUTS-2 region in the UK for the period 2000-2011.

²²Estimations 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.

²³The total employment data differ only slightly between the European and the UK labour force.

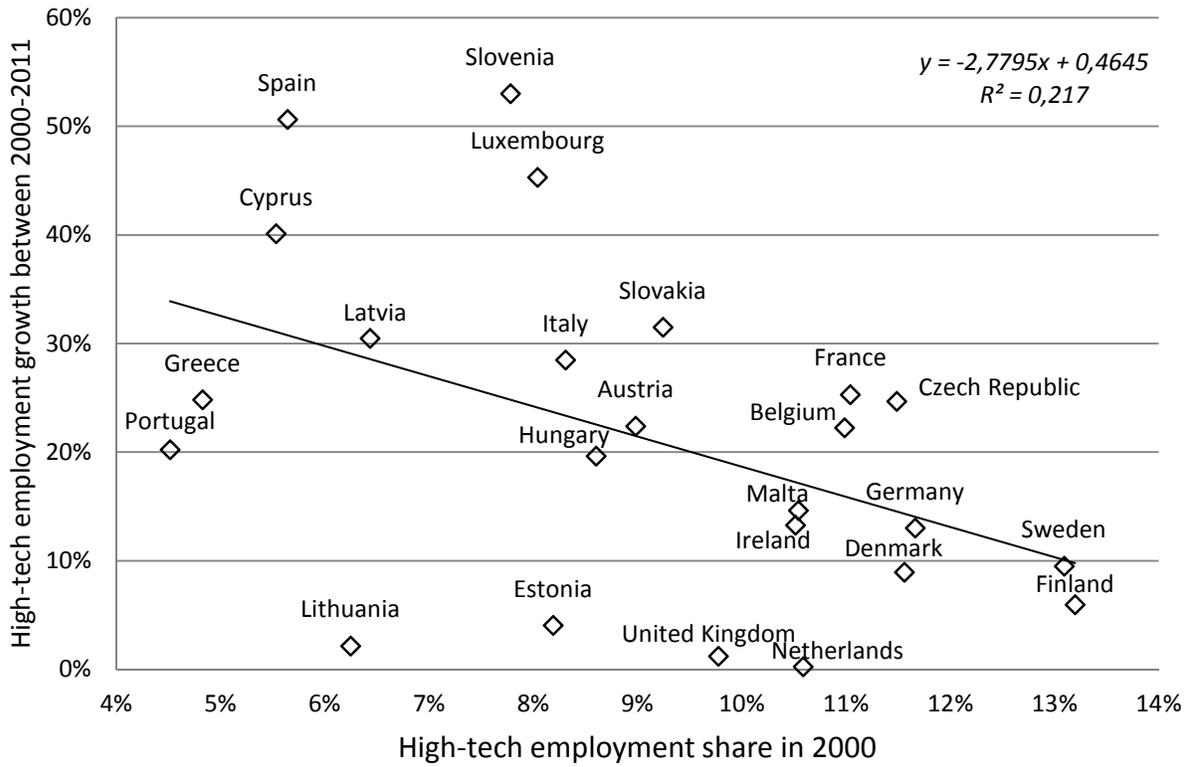
²⁴Though the high-tech employment data from the European LFS and the UK LFS show substantial differences, the distribution of HT employment over the NUTS-1 regions is very similar. We therefore assume that the distribution over the NUTS-2 regions will also be reliable.

Figure 1: Cumulative Employment growth: total versus high-tech (in %, EU-27, 2000-2011)



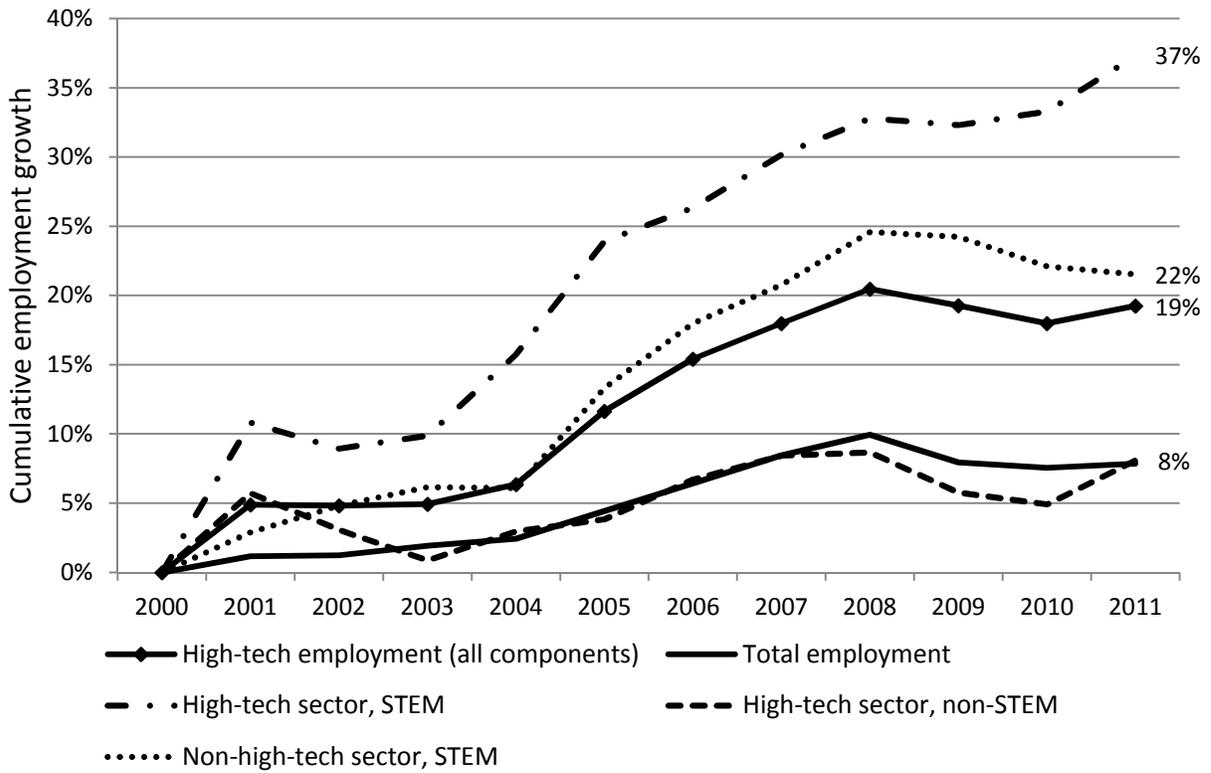
Notes: In the years before total country coverage (2000-2004) EU-27 high-tech employment is calculated as the share of high-tech employment in the covered countries multiplied by total EU-27 employment.

Figure 2: High-tech employment intensity and growth per country (in %, 2000-2011)



Notes: Bulgaria, Romania and Poland excluded because of missing data in 2000

Figure 3: 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.

Figure 4: High-tech intensity per NUTS-2 region (in %, 2011)

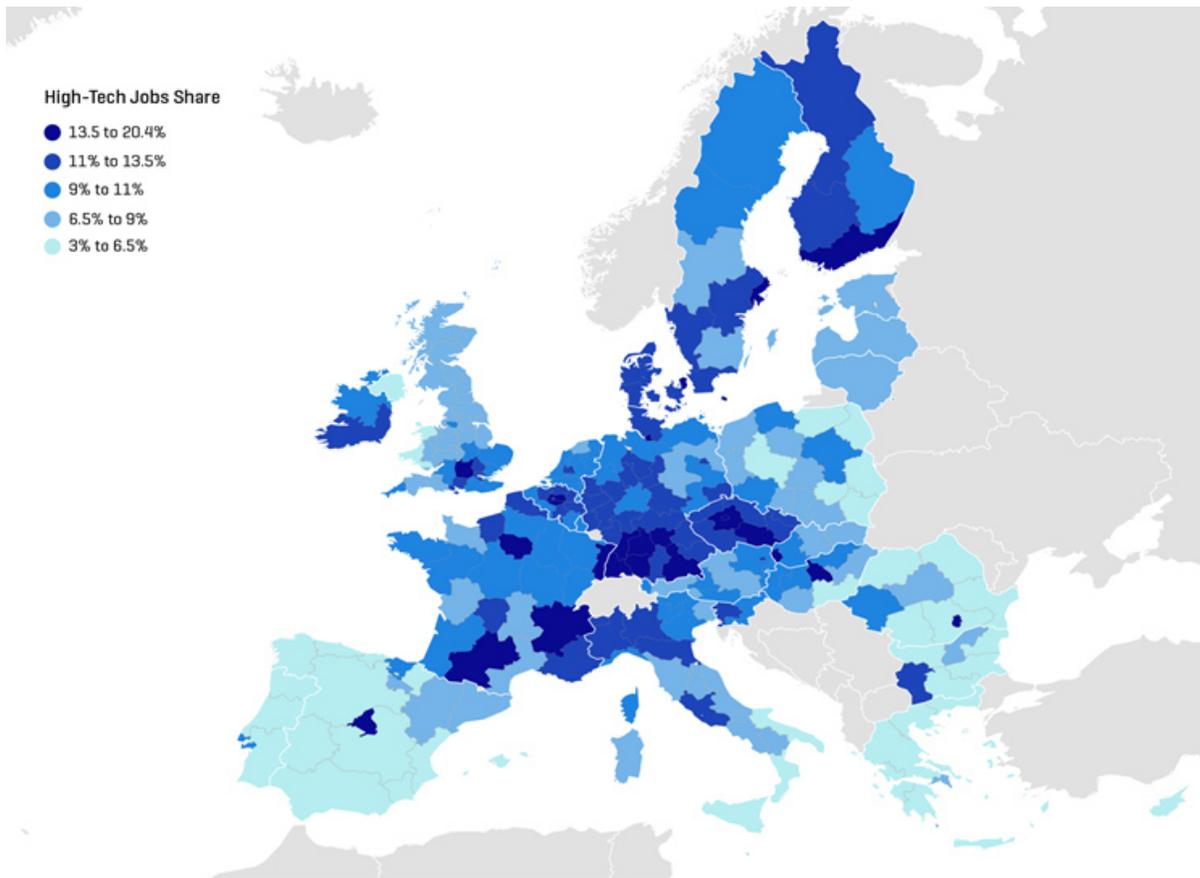
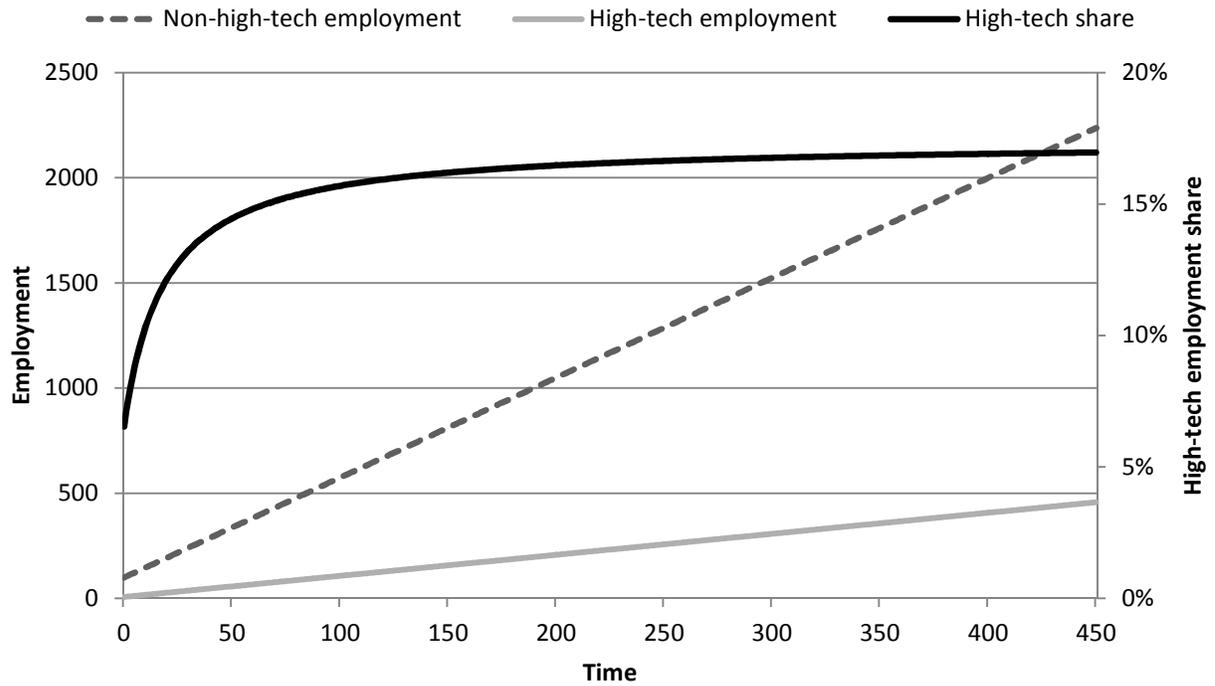
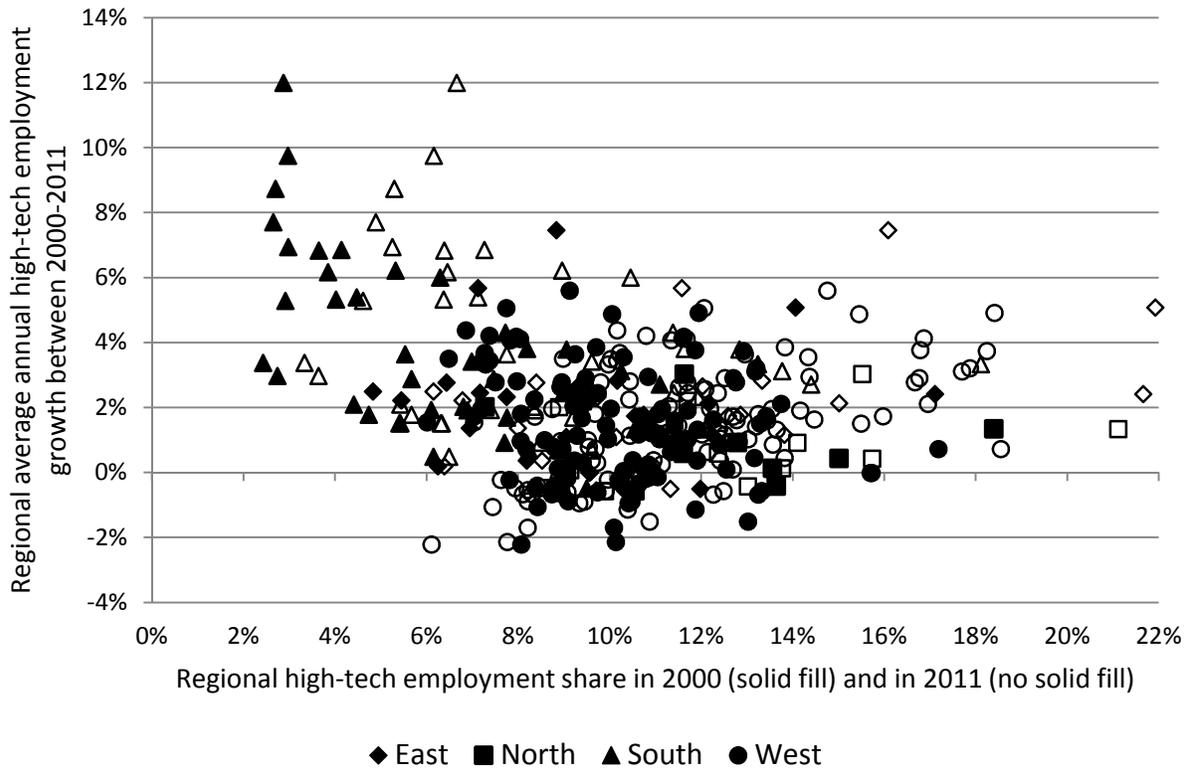


Figure 5: Simulation of high-tech employment share evolution



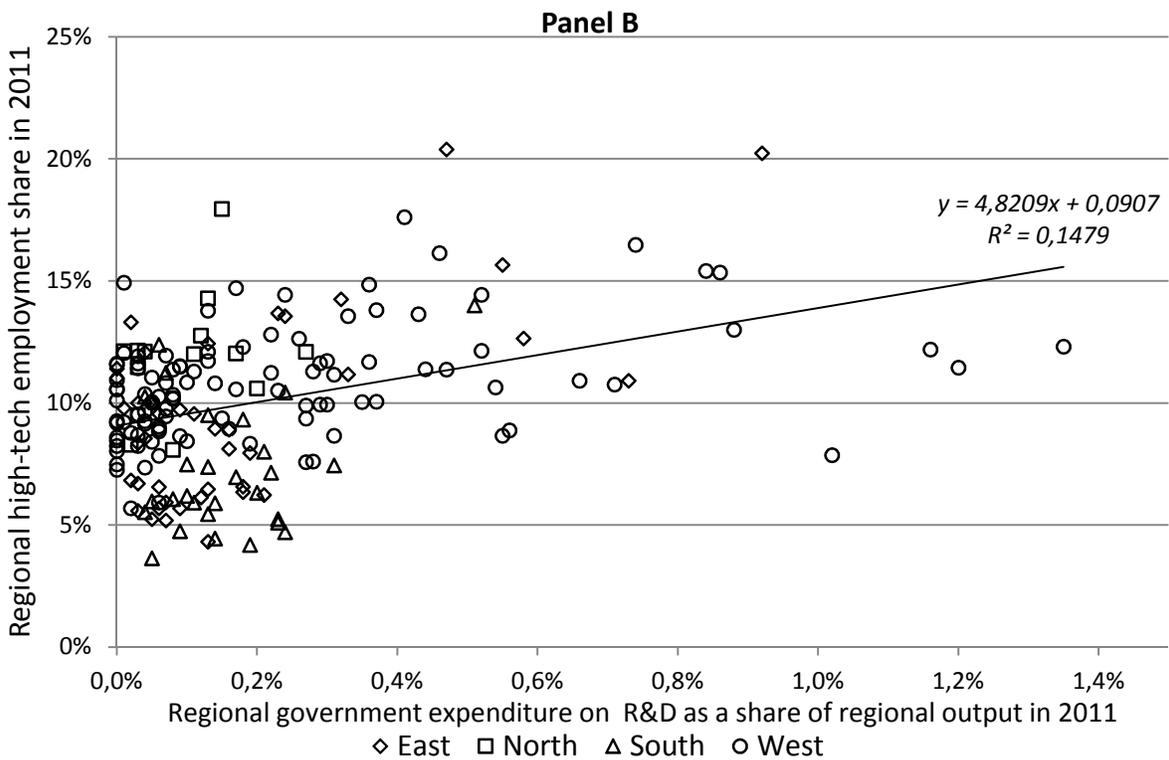
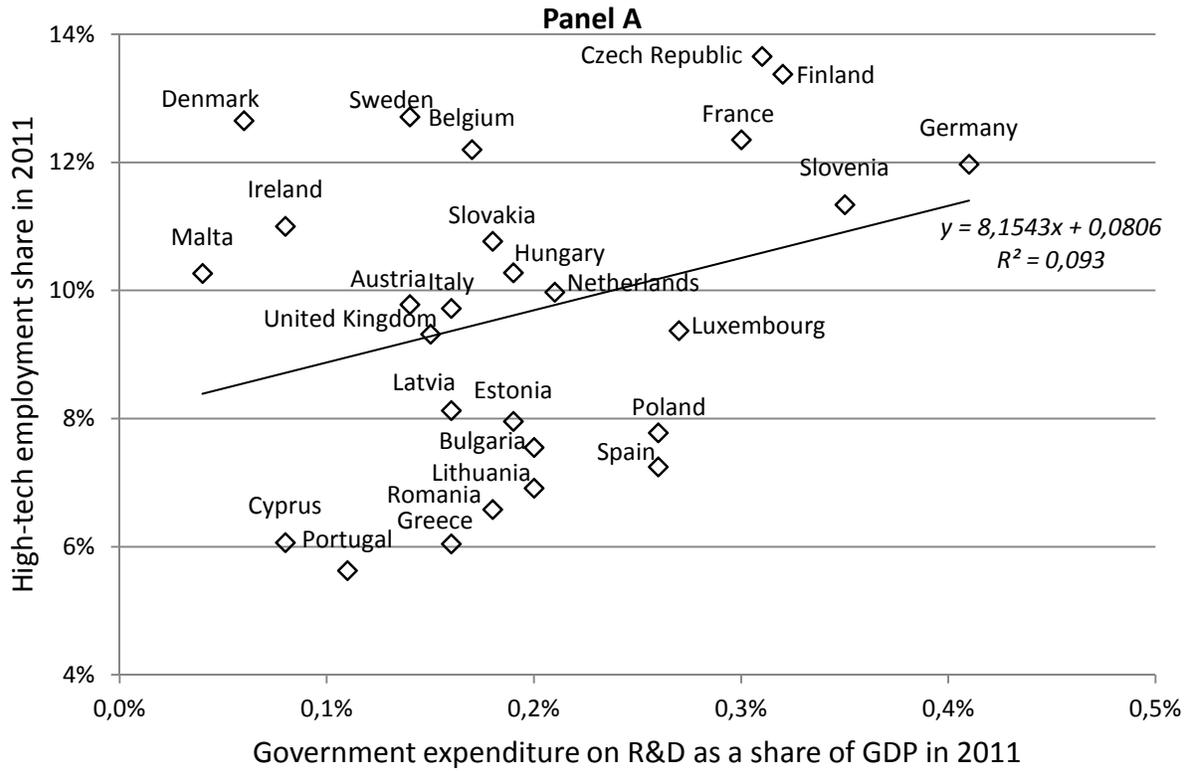
Notes: Initial (t=0) high-tech share of 7% assumed. In each period the number of high-tech jobs increases by 1, with a multiplier of 4.75.

Figure 6: High-tech intensity and growth per NUTS-2 region (in %, 2000-2011)



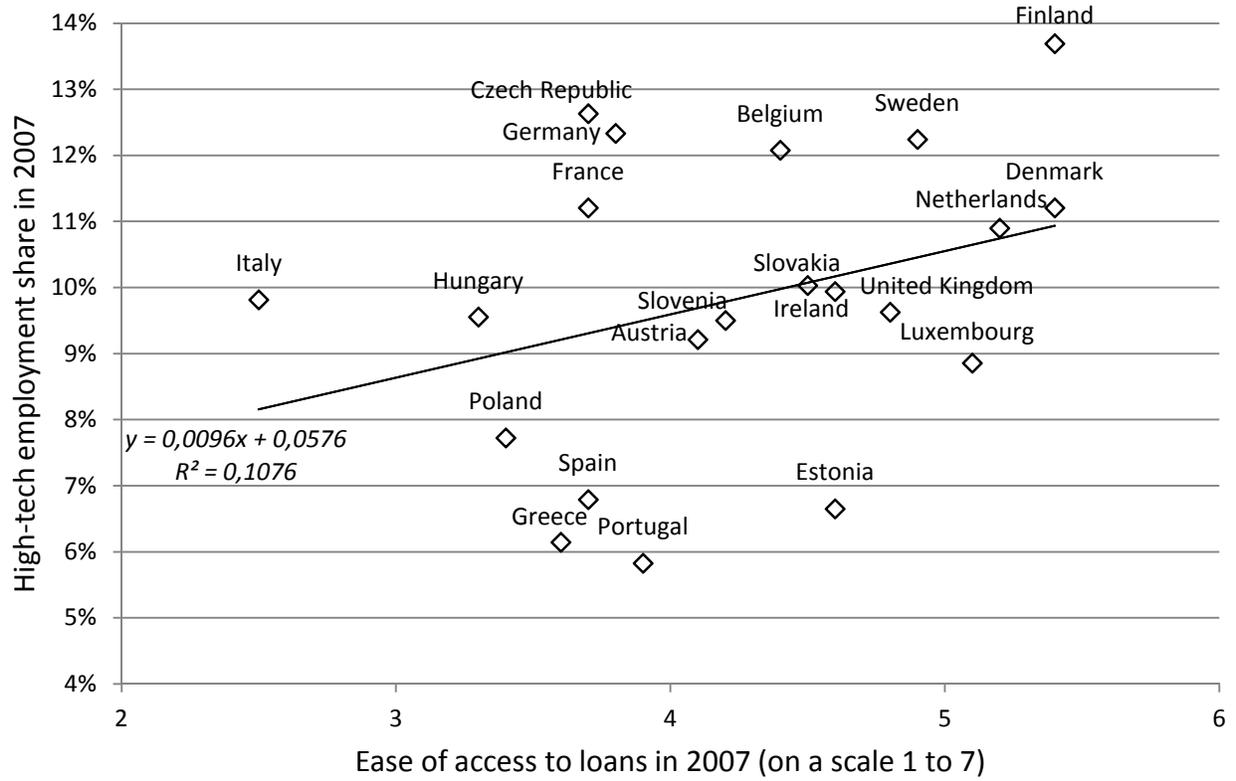
Notes: Only regions with non-missing observations in 2000 and 2011 included

Figure 7: High-tech intensity versus Government expenditure on R&D (in %, 2011)



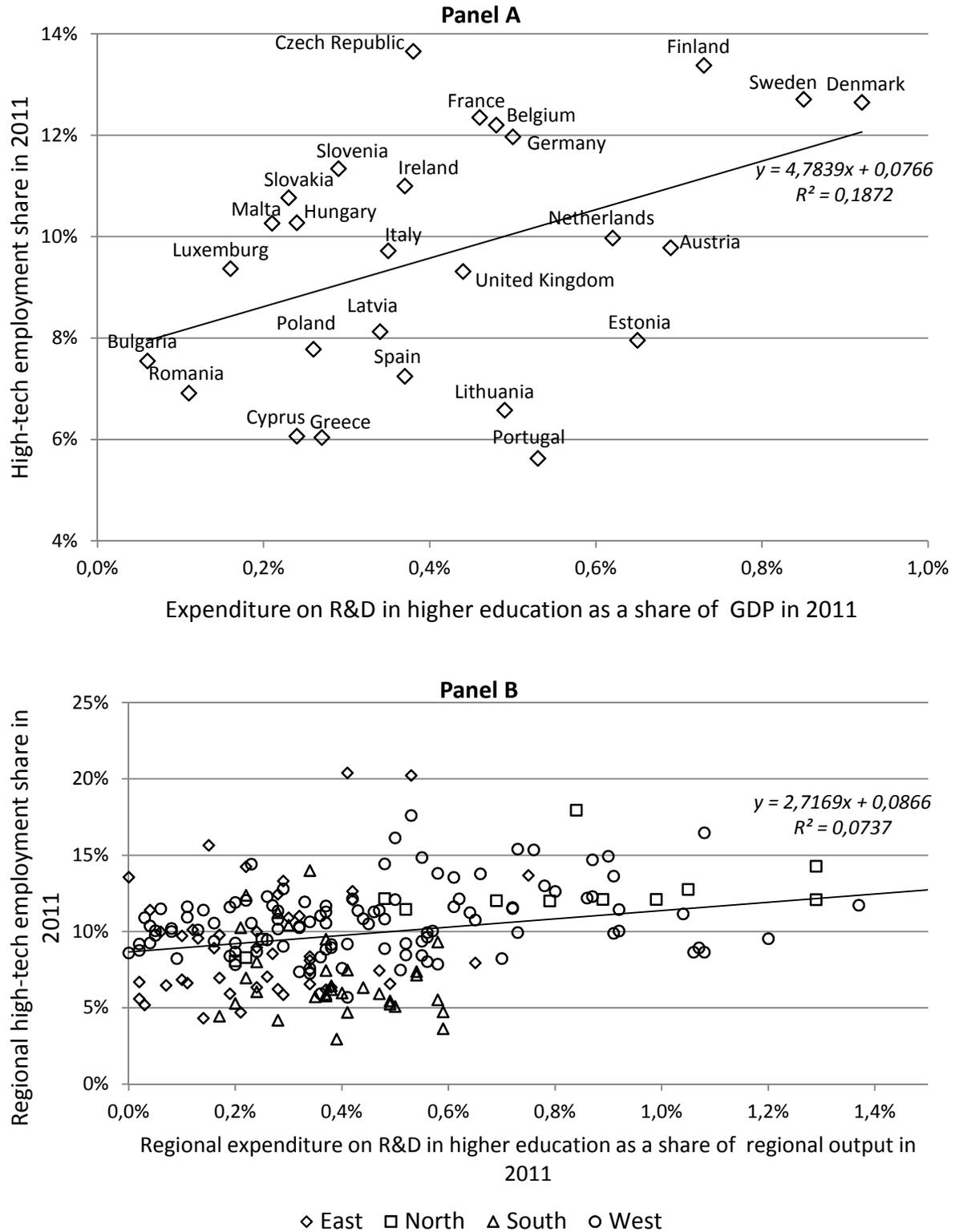
Source: R&D expenditure from Eurostat

Figure 8: High-tech intensity versus ease of access to bank loans (2007)



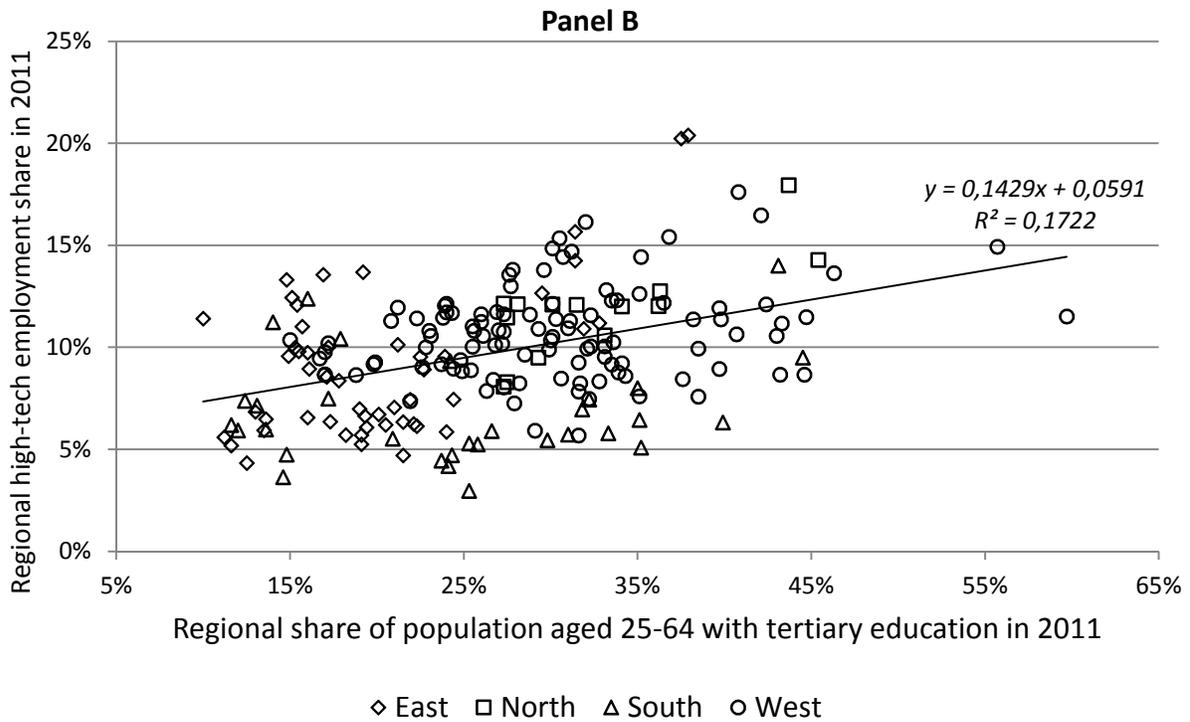
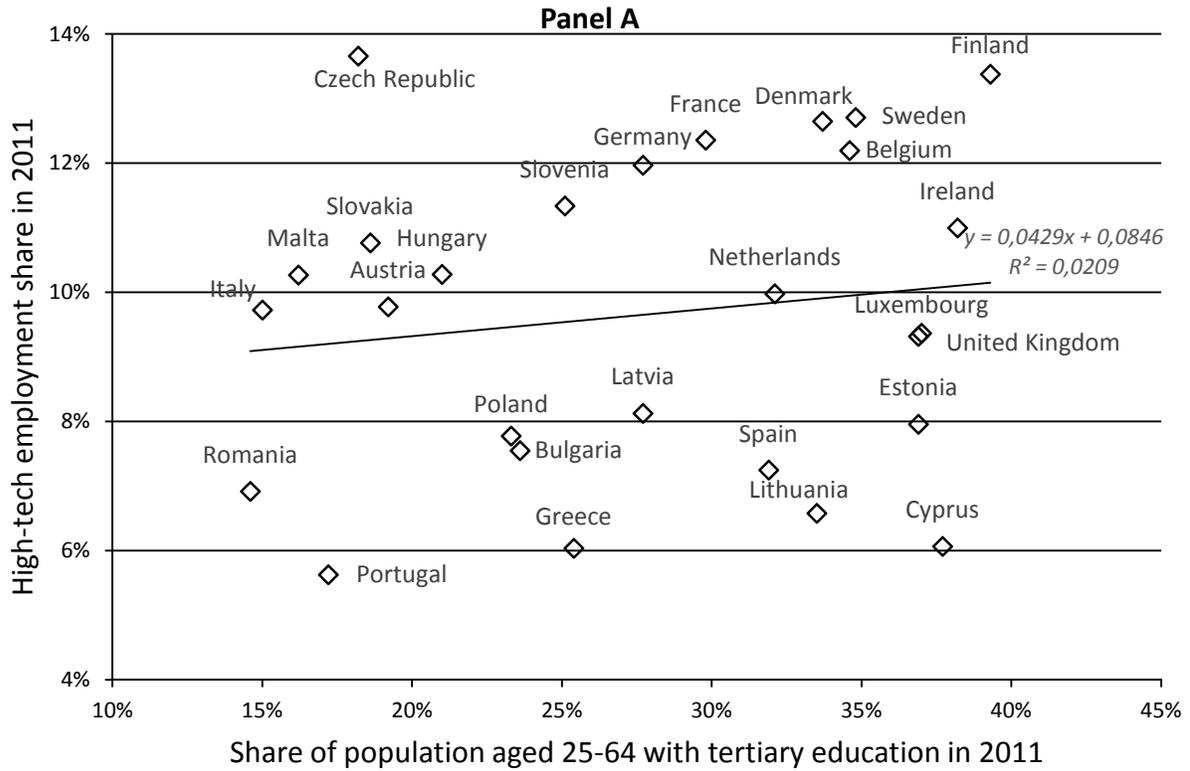
Source: Ease of access to bank loans from OECD science, technology and industry scoreboard 2013.

Figure 9: High-tech intensity versus R&D expenditure in higher education (in %, 2011)



Source: R&D expenditure from Eurostat

Figure 10: High-tech intensity versus tertiary education share (in %, 2011)



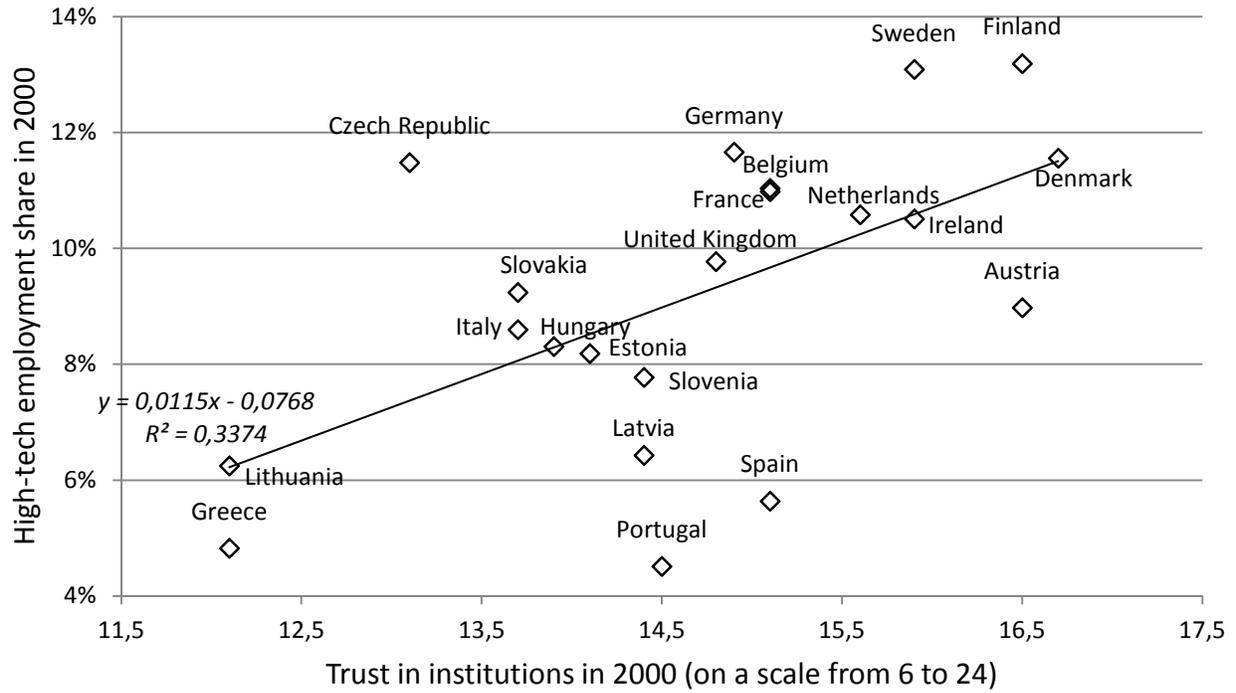
Notes: Tertiary education share from Eurostat

Figure 11: High-tech intensity versus active participation in voluntary organizations (2000)



Source: Active participation from van Oorschot, Arts and Gelissen (2006)

Figure 12: High-tech intensity versus trust in institutions



Source: Trust in institutions from van Oorschot, Arts and Gelissen (2006).

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)

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

NUTS-2 region	Total employment in 2011 (in 000s)	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. Andalucía (Spain)	2774	5.3%
6. Comunidad 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%

Table 3: Multiplier regression results

	High-tech employment				STEM employment	
	OLS	Eq. (3)	IV Eq. (4)	Eqs. (3) and (4)	OLS	IV Eq. (3)
Estimated local multiplier	2.57* (0.58)	4.75* (1.12)	4.78* (1.13)	4.77* (1.13)	2.80* (0.67)	4.45* (1.23)
<i>Number of observations</i>	410	398	398	398	410	398
	IV first-stage coefficients					
Eq. (3)	-	0.53* (0.14)	-	0.04 (0.79)	-	0.54* (0.17)
Eq. (4)	-	-	0.56* (0.13)	0.51 (0.74)	-	-

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.

Table 4: Convergence regression results

	NUTS-2			NUTS-1		
	1-year differences	5-year differences	10-year difference	1-year differences	5-year differences	10-year difference
ln(high-tech employment share in a previous period)	-1.07* (0.2)	-4.44* (0.89)	-7.56* (1.62)	-0.73* (0.27)	-3.91* (1.32)	-6.79* (1.83)
Year fixed effects:						
2002	-4.19* (0.87)	-	-	-4.41* (1.13)	-	-
2003	-2.72* (0.92)	-	-	-3.32* (1.03)	-	-
2004	-3.03* (0.87)	-	-	-1.76 (1.03)	-	-
2005	-0.31 (0.90)	-	-	-0.08 (1.10)	-	-
2006	-1.69 (0.89)	4.02* (1.53)	-	-0.52 (1.10)	3.94 (2.26)	-
2007	-0.61 (0.88)	-	-	-0.88 (1.07)	-	-
2008	-2.55* (0.87)	-	-	-1.77 (1.05)	-	-
2009	-5.20* (0.87)	-	-	-5.53* (1.06)	-	-
2010	-5.47* (0.94)	-	-	-3.88* (1.17)	-	-
2011	-3.22* (0.72)	-	-	-3.31* (0.75)	-	-
Constant	8.93* (1.20)	23.82* (3.94)	44.75* (7.11)	7.90* (1.50)	25.02* (7.06)	47.60* (9.87)
<i>Number of observations</i>	2358	413	186	942	169	78
<i>Speed of convergence (in %)</i>	1.07	0.89	0.79	0.70	0.79	0.70
<i>Time-to-half (in years)</i>	63	77	88	99	87	98

Notes: The dependent variable is ln(high-tech employment share). All coefficients and standard errors have been multiplied by 100. * Significant at the 1% level.