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Technological invention and local labour markets: Evidence from France, Germany and the UK

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ABSTRACT

I estimate employment multiplier effects by skill group from graduate employment and innovation at the NUTS1 and 2 level in France, Germany and the UK. Using local projections, I estimate the effects over 5-year horizons. Both graduate employment and patenting have temporary, positive impacts on non-graduate and mid-skilled employment. There is considerable heterogeneity in terms of the direction and magnitude of the effects across the three countries. The paper shows that innovation can be a source of regional employment growth, even for those without a graduate degree.

1. Introduction

With a returning interest in industrial strategy, many governments seek to foster technological invention as a local economic development strategy. The rationale behind this policy approach is two-fold: On the one hand, it is a well-established fact in economic theory that technological progress drives economic growth in the long run (Aghion and Howitt, 1990). On the other hand, innovative and high-tech sectors have multiplier effects, implying that through their spending on local services, highly paid workers at innovative firms generate further jobs in the local economy, in particular for non-graduates (Moretti, 2012). Therefore, when assessing the local labour market effects of innovation, many scholars focus on the impact of the number of high-skilled workers on other employment (e.g. Kemeny and Osman, 2018; Lee and Clarke, 2019; Lee and Rodríguez-Pose, 2016). However, there is less evidence on the direct impacts of invention and innovation activity on local labour markets, other than mediated through employment multipliers.

Classic models have focused on a dichotomy between “high” and “low” skilled workers. However, recent evidence of routine-biased technical change suggests that jobs in the middle of the income distribution are declining, as they often comprise of routine activities that are easily automated (Autor, 2019; Goos et al., 2014; Harrigan et al., 2021). Indeed, a downside of innovation may be that it leads to further automation and job losses, particularly in manufacturing (Acemoglu et al., 2020; Acemoglu and Restrepo, 2020). Yet, technological invention may also provide a source of job growth for mid-skilled workers in occupations that require creativity and soft skills (Aghion et al., 2019). This would be the case in particular when implementing new technologies that are not yet standardised and therefore not automatable. Invention may reverse some of the effects of routine-biased technical change, as it creates demand for activities that are non-routine. There is little evidence of the local labour market effects of innovation on employment by level of education, a gap that this paper seeks to fill.

This paper studies the effects of technological invention, measured by patent filings, on regional employment in France, Germany and the UK. I distinguish between three skill groups: graduates, all non-graduates, as well as those with advanced vocational qualifications below degree level (henceforth also called “mid-skilled”). I estimate these effects with the help of panel data for the period between 2000 and 2019 at the level of NUTS 1 and 2 regions. I use local projections

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estimation (Jordà, 2005) to trace out the effects of changes in patenting and graduate employment on non-graduate and mid-skilled employment over a period of one to six years and calculate multiplier effects of the additional jobs created. In terms of magnitudes, patenting can account for 0.07% of total graduate employment, 0.01% of non-graduate employment and 0.05%, while graduate employment accounts for 5% of total non-graduate employment. These magnitudes are somewhat smaller than those commonly found in the literature (e.g. Lee and Clarke, 2019; Moretti, 2012). I also investigate heterogeneity across the three countries in the sample. While these three large, developed economies are the most innovative in Europe in terms of patent filings, they are very different in terms of their innovation systems and labour market institutions, factors that mediate the effects. The diversity across these three countries also means that the results hold relevance for countries with similar innovation systems, including industrial structures, education systems and employment relations, with the German economy to a large extend resembling that of Nordic countries, France that of the Southern European periphery and the UK being comparable to the US. However, given the nature of the patenting data used, results will be less relevant to low- and middle-income countries that are relatively far from the technological frontier and generally patenting less.

The paper contributes to the large literature on innovation-employment multipliers (Brenner et al., 2018; Eberle et al., 2020; Frocrain and Gitraud, 2018; Kemeny and Osman, 2018; Lee and Clarke, 2019; Moretti, 2010; Moretti and Thulin, 2013; Van Dijk, 2018; Van Roy et al., 2018). In contrast to the existing literature, it considers and compares the effects across three skill groups and three countries. Furthermore, the estimation strategy provides the adjustment in employment in response to shocks over several years, rather than a single point in time. The results show that, while growth in graduate employment is relatively persistent, gains in non-graduate and mid-skilled employment tend to be short-lived, with employment reverting to the baseline within two to three years.

The paper identifies lessons for policy makers: First, it demonstrates that innovation can create employment opportunities also for workers without degree-level education. However, the effects are larger for those with vocational skills than those without post-secondary qualifications. This suggests that innovation and skills policy need to be considered in conjunction. Second, the results show that multiplier effects decline over time. This provides important context to some of the large multiplier effects found in the literature (e.g. Moretti, 2012). Benefits of innovation decline or disappear again within a matter of years, highlighting the importance of creating an environment that is supportive of continuous innovation. Third, the effects are mediated by underlying institutions, as shown by the considerable variations in the results across the three countries studied.

The paper proceeds as follows. Section 2 reviews the relevant literature to contextualise the analysis. Section 3 describes the dataset and introduces the estimation strategy. Section 4 provides the results. Section 5 concludes.

2. Related literature

In the following, I present a review of the literature on labour market impacts of patenting, invention and innovation, situating this in the contexts of the three countries studied. The shortcomings of relying solely on patents as a measure of invention are discussed in Section 3.

2.1. Innovation multiplier effects

The idea that employment creation in some sectors increases employment in others is well established, going back to North (1955). Theory predicts that tradable industries create employment in non-tradable industries, either through direct links such as local distribution and business services, or indirectly, through the consumption of local services by those employed in the tradable industry (Moretti, 2012). Recent evidence confirms the significance of the multiplier effect for regional growth (Moretti, 2010; Moretti and Thulin, 2013; Frocrain and Gitraud, 2018), although its magnitude remains somewhat disputed (Van Dijk, 2018).

In this context, invention and innovation play important roles because of the rents that creators of new ideas are able to capture. Invention, measured by patenting, relies on highly skilled workers who receive a share of these rents (Van Reenen, 1996; Kline et al., 2019). The comparative advantage that patenting firms enjoy allows them to grow, leading to higher employment at the individual firm level (Balasubramanian and Sivadasan, 2011; Van Roy et al., 2018).

Wider regional effects of innovation are generally conceptualised in terms of consumption multipliers. In this respect, innovative industries are not very different from other industries relying heavily on high-skilled, highly paid workers, such as knowledge-intensive business services (Brenner et al., 2018). Indeed, there is evidence that high-tech industries contribute to the polarisation of labour markets by creating a lot of employment in local service industries (Kemeny and Osman, 2018), jobs that are often low paid (Lee and Clarke, 2019).

However, the effects of innovation can go beyond the consumption channel, as patenting firms fuel further research and development activity at the regional level, and create further employment in innovative industries (Buerger et al., 2012). Innovative regions attract graduates that contribute to a virtuous cycle of innovativeness, employment growth, and human capital accumulation (Faggian and McCann, 2009). Yet, innovation may contribute to growing polarisation between innovative, fast-growing regions that attract skilled workers, and those that are left behind (Autor, 2019; Rodríguez-Pose, 2018).

Nonetheless, innovation may also directly benefit those with qualifications below degree level (Filippetti and Guy, 2016). After all, not all workers involved in innovation and innovative industries are high-skilled. Aghion et al. (2019) find that low-skilled workers benefit from innovation at the firm level in terms of higher wages, in particular in jobs reliant on soft skills.

Polarisation of labour markets with growth concentrated in both high- and low-paid non-routine occupations has been driven by skill-biased technical change and offshoring which has eliminated many mid-skilled routine occupations in high-income economies (Autor and Dorn, 2013; Caselli and Manning, 2019; Cortés, 2008; Gagliardi et al., 2021; Goos et al., 2014). In contrast to low-skilled occupations, mid-skilled occupations that were lost in manufacturing sectors have not been replaced in the service economy. By virtue of their newness, tasks in innovative industries are less likely to be automatable, at least in the medium term. Following a successful patent filing, the composition of new hires tends to reflect a firm's previous skill profile, indicating no evidence of a skill bias of invention at the firm level (Kline et al., 2019). This is also supported by theories of industry life cycles, whereby industries are most agglomerated during the most innovative stages before offshoring and outsourcing take over in more mature phases (Audretsch and Feldman, 1996a). However, the degree to which benefits of innovation are shared across skill groups depends on the institutional and wider policy environment (Bramwell, 2021; Ciarli et al., 2018). This also suggests that any multiplier effects may be temporary. Once a technology matures, it would be expected that production is either automated or moves to a lower-cost location. The employment that was created as a result of the invention would then disappear again.

2.2. National innovation and education systems

While innovation may be a source of employment growth, skilled workers are also an important input in the innovation process (Gagliardi, 2014; Faggian et al., 2017), and collaborations between universities and industry are a driver of local innovation (Crescenzi et al., 2017; D'Este et al., 2013). Regions with abundant human capital therefore attract innovative activities, which may reinforce inequalities between regions. Furthermore, R&D-intensive industries tend to cluster more than other industries (Audretsch and Feldman, 1996b). This is because of the strong path dependency in knowledge creation and the small radius in which knowledge spillovers tend to occur (Sonn and Storper, 2008). Where exactly innovative activities locate and thrive remains a topic of intense scholarly debate, with factors including local and national institutions, skills and serendipity all playing a role (Chatterji et al., 2014; Storper et al., 2015). While lagging regions need to invest in innovation to catch up with leaders, they often lack the absorptive capacity to do so, further widening the divide (Muscio et al., 2015).

The three countries included in the empirical analysis are deliberately chosen to represent different types of national innovation systems, in particular with reference to education systems and labour market flexibility. Among the three countries, France has the most stringent employment protection laws, while the UK has the most liberal. German labour market institutions used to resemble the French, but have been somewhat liberalised in recent years (Griffith and Macartney, 2014).

There are significant differences in terms of education systems. Germany has a strong tradition of vocational post-secondary education of the "dual apprenticeship" model, whereby apprentices spend some time acquiring firm-specific skills while training on the job, and the rest of their time acquiring transferable skills at a further education college. In contrast, while the French education model also provides a range of post-secondary qualifications below degree level, skills tend to be acquired on the job with company-based training. In the UK, further education is weak, with mostly college based training (Esteves-Abe et al., 2001). Instead, access to higher education has been promoted, so that the share of university graduates in the workforce is comparatively high in the UK.

This affects the quality of jobs that are created through innovations, as Kemeny and Osman (2018) and Lee and Clarke (2019) find that jobs created through the multiplier effect from high-tech employment may have an overall negative effect on average earnings in liberal labour market regimes such as in the US and the UK. As Lee (2024) shows, countries that foster more 'inclusive' innovation, creating employment for mid-skilled workers, have strong vocational education models that are responsive to employers' skill needs. Vocational skills tend to be more industry and firm-specific, creating a wider variety of skills that is conducive to innovation (Filippetti and Guy, 2016). Employment protection affects the degree and speed of adjustment following a technological shock. The multiplier effect may be less pronounced if hiring is costly or workers lack the right skills to fill roles. Highly specialised skills make it harder to adjust in the face of technological and organisational change (Lamo et al., 2011). Employment protection legislation that makes it harder to hire and fire workers may provide an incentive for firms to innovate to improve productivity in an otherwise inflexible setting. However, rigid institutions also make workforce adjustment harder if skill requirements change due to technological progress. The evidence suggests that there is more innovation overall in countries with stronger employment protection, but this tends to be incremental, whereas countries with liberal labour market institutions tend to be drivers of radical innovation (Akkermans et al., 2009; Griffith and Macartney, 2014).

3. Data and empirical methods

The following describes the dataset used in the analysis. Patent data are readily available as an imperfect but consistent proxy measure of invention. Measures of employment by skill level are more difficult to harmonise across the three countries and over time.

3.1. Measuring technological invention

The OECD REGPAT database provides patents matched to NUTS regions, which can be used as a measure of local inventions (OECD, 2021). The database covers all patents filed with the European Patent Office (EPO) as well as those filed under the Patent Co-operation Treaty (PCT) after 1977. Following Sonn and Storper (2008), I use the inventor location to assign patents to a region, as this is most likely where the innovative activity has taken place. If there are multiple inventors in different regions, the patent is counted fractionally. The number of patents applied for during a given year by local inventors is then the measure of regional inventiveness. While the application date is used as the date of the invention, only applications that are ultimately successful are included in the dataset.

While widely used for research purposes, patents are a noisy measure of invention. On the one hand, many patents are not very valuable commercially (Hall et al., 2001; Pakes, 1984). On the other hand, many valuable ideas are not or cannot be patented for various reasons. Patents apply mainly to product innovation, and therefore do not measure process innovation. They only represent the first stage in the innovation process, with many inventions never being commercialised (Carlino and Kerr, 2015). The further innovation process after the registration of a patent may also take place in a different location from the invention itself (Feldman, 1994). Patents are less applicable to service industries, although patents can be granted for software code. That being said, in cross-country comparisons, patents capture variation in research productivity (de Rassenfosse and van Pottelsberghe de la Potterie, 2009), and have direct impact on firm-level employment, productivity and wages (Kline et al., 2019; Van Reenen, 1996).

3.2. Employment by education levels

The diversity of national education systems and qualifications used across the three countries poses a challenge to measuring employment by educational attainment at a fine-grained level. There is a trade-off between availability of regional data at small spatial scales and more detailed educational information. The analysis deals with these issues by combining two different datasets.

The first dataset, provided by Eurostat, provides employment by broad educational attainment at the NUTS2 regional level (Eurostat, 2020a). The three classifications available are tertiary, upper secondary, and primary/lower secondary. Those with secondary education form the non-graduates group for the analysis, while those with tertiary education are deemed graduates. Consistent estimates for the three countries are available from 1999 to 2019. The classification is a rough approximation of skill levels. It is noticeable that the share of graduates in Germany is overall lower than that in Great Britain or France as vocational degrees are more prevalent.

The second dataset is based on the European Social Survey (ESS) to construct an intermediate group with advanced vocational education (Core Scientific Team of the ESS, 2018). Skills of this category are often instrumental to the commercialisation of new technologies and technology-based businesses (Lowe, 2021). However, they are also much more diverse, encompassing a plethora of degrees and accreditations that differ across the three countries. For example, in Germany, further education is most standardised, with accredited apprenticeships the most common avenue. In the UK in contrast, further education is more likely to be college-based, with practical training happening on the job (Esteves-Abe et al., 2001). Often, skills are not formalised at all and acquired on the job, making them, in the words of Lowe (2021), 'ambiguous'.

In the Eurostat data, this group is split between the graduate and non-graduate groups. The ESS is a household survey that has been conducted every two years since 2002, providing nine survey waves to date. The survey asks respondents about their educational attainment

Table 1
Intermediate education category.

France	Germany	UK
First university degree (premier cycle)	Master craftsman, technician or equivalent college diploma	Nursing certificate
Elementary diplomas in law and pedagogy	Apprenticeship in commerce, industry, crafts or agriculture	Teacher training
Professional and technical vocational degrees (brevet)	College degrees in pedagogy, nursing and other medical assistant professions Elementary civil service exams (Laufbahnprüfung)	Technical diplomas

Note: National qualifications included in the ISCED IV — advanced vocational, sub-degree category. Includes most relevant categories only.

as well as – if applicable – that of their partner. Responses are coded to the International Standard Classification of Education (ISCED), but the original responses according to national standards are also retained. The level of detail and classifications available varies over time, also in response to changes in national education systems. As a baseline, I use ISCED IV – advanced vocational, sub-degree – as the definition for the intermediate education category. For more recent surveys, all education levels are coded to harmonised ISCED levels. However, in the four surveys between 2002 and 2008, this is not always the case and gaps have to be filled manually. Table 1 gives an overview of the qualifications making up the intermediate category.

While the ESS is a household survey and responses are at the individual level, these can be aggregated into regional totals. Geographical information is available at the NUTS1 level, i.e. larger regions than the NUTS2 regions available on the Eurostat dataset. To make full use of the available data, I consider both respondents as well as information available on their partners so that the total working population is made up of working respondents and working partners of respondents. Partners are assigned the same weight as respondents. In some regions, there is a lot of fluctuation in sample sizes between waves of surveys, resulting in even larger variations in the number of those with vocational qualifications. To reduce the survey variation, I normalise the number of employees by total Eurostat employment according to Eq. (1), multiplying the raw number of mid-skilled workers, $emp^{mid-raw}$ as a share of total employment in the ESS, emp^{ESS} by total employment from Eurostat. This normalisation is not required for the non-graduate and graduate variables, as these are available as aggregated population totals.

$$emp^{mid} = \frac{emp^{mid-raw}}{emp^{ESS}} * emp^{Eurostat} \tag{1}$$

As NUTS2 regions are nested in NUTS1 regions, it is easy to aggregate variables available from Eurostat into the NUTS1 regions available on the ESS, so that all variables used in the analysis involving ESS variables are at the same regional level. The ESS provides a more detailed categorisation of education and qualification levels than the Eurostat dataset. However, the limited number of survey waves available results in less precise estimates from time series analysis using the dataset. Therefore, I only use the ESS dataset to estimate the intermediate skill category, which is not available from Eurostat.

3.3. Estimation strategy

Estimating the effects of innovation on regional employment is challenging because of the endogeneity of all variables involved. Innovation may create jobs, but also depends on the availability of local skills. Furthermore, high-skilled workers may be directly responsible for the creation of lower-skilled jobs through the consumption channel. I rely on the panel aspect of the data to deal with these issues.

For all variables, I estimate the effect over increasing time horizons to trace the cumulative effect of the explanatory variables over time, following the local projections approach by Jordà (2005). The method can be used to estimate impulse response functions for multivariate dynamic systems, similar to vector autoregression (VAR). Indeed, many studies use VAR estimation in similar contexts (e.g. Brenner et al., 2018; Buerger et al., 2012; Eberle et al., 2020). However, the local projection estimates are more robust to misspecification and can be estimated by OLS (Jordà, 2005). While a VAR relies on extrapolation of impulse responses from lagged effects, the local projection method explicitly estimates effects at different forecast horizons. Other studies estimate multiplier effects for single points in time (e.g. Kemeny and Osman, 2018; Lee and Clarke, 2019). However, that approach cannot reveal information about the dynamics of the multiplier effect. As I will show below, the effect can take some time to materialise, and also disappear again after a few years.

Eq. (2) specifies the estimating equation for the effect of patenting on graduate employment growth. $emp^{g}_{r,t+h} - emp^{g}_{r,t-1}$ is the log difference in graduate employment in region r between $t-1$ and $t+h$. pat_{t-1} is the number of patents filed in t−1 in logs, $emp^{g}_{t-1,t-2}$ are lags of the dependent variable, and $X_{r,t}$ are additional control variables. In particular, I control for population density (Eurostat, 2020b) and a dummy variable equal to 1 in 2009 and 2010 during the recession following the financial crisis. Region fixed effects α_r control for unobservable differences in regions that are invariant over time. Of particular concern are differences in economic structures with some regions specialising in industries that are innovative, but less prone to patenting, such as software development and service industries. These structural characteristics of regions change relatively slowly, so that fixed effects can to some extent control for this.

$$emp^{g}_{r,t+h} - emp^{g}_{r,t-1} = \beta_0 + \beta_h pat_{r,t-1} + emp^{g}_{r,t-1,t-2} + \gamma X_{r,t} + \alpha_r + \epsilon_{r,t} \tag{2}$$

I estimate this model for h running from −4 to 5 to trace out the effect of patenting on employment over time. The negative lags test for a placebo effect: If there was already an effect detectable before the patenting shock occurs, it would suggest that an underlying unobserved variable is causing both the patenting and the graduate employment shock. To visualise the impulse response, I plot the β_h against the time horizon effectively tracing the cumulative effect of the patenting shock over time.

Effects on the other variables are estimated analogously. Eq. (3) specifies the effect of graduate employment and patenting on non-graduate employment. Here, non-graduate employment growth, $emp^{ng}_{r,t+h} - emp^{ng}_{r,t-1}$ is estimated as a function of graduate employment growth, where Δemp^{g}_{t-1} is the log difference in graduate employment between t−1 and t-2, and the number of patents filed in a year, pat_{t-1}, in logs.

$$emp^{ng}_{r,t+h} - emp^{ng}_{r,t-1} = \beta_0 + \beta^{g}_{h} \Delta emp^{g}_{r,t-1} + \beta^{p}_{h} pat_{r,t-1} + emp^{ng}_{r,t-1,t-2} + \gamma X_{r,t} + \alpha_r + \epsilon_{r,t} \tag{3}$$

The estimating equation for higher vocational or mid-skilled employment, Eq. (4), accounts for the fact that employment estimates in this category are only available in two-year intervals as explained above. Graduate employment is included as the two-year growth rate and patenting as the total over two years. I estimate this equation for h running from −3 to 3.

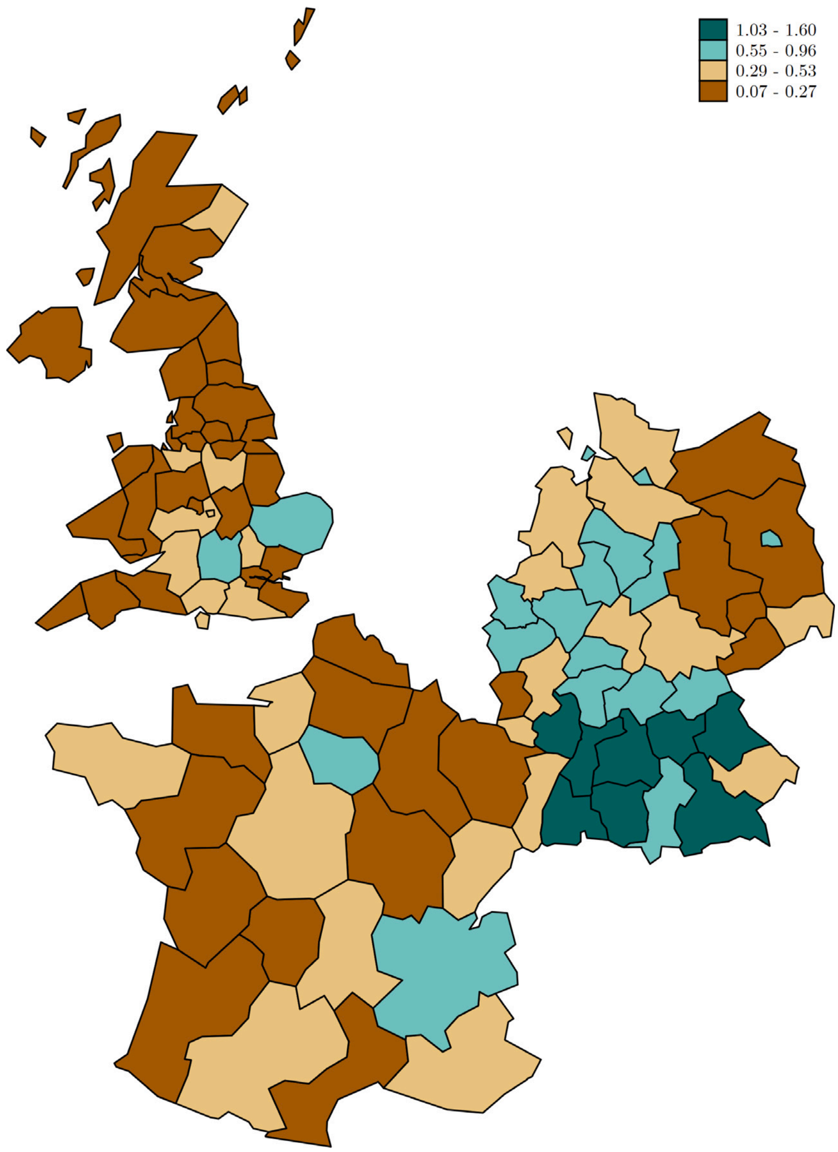

Fig. 1. Patent applications per 1000 employees. *Note:* Average for 2000–2017, NUTS2 regions.

$$emp^{mid}_{r,t+2h} - emp^{ng}_{r,t-2} = \beta_0 + \beta^g_h \Delta emp^g_{r,t-2} + \beta^p_h (pat_{r,t-1} + pat_{r,t-2}) + \Delta emp^{mid}_{r,t-2} + \gamma X_{r,t} + \alpha_r + \epsilon_{r,t} \quad (4)$$

As noted before, causal identification of these effects is challenging, because of the interdependence of the variables. The placebo test checks for reverse causality, as changes in the dependent variable cannot feasibly be caused by future changes in the explanatory variable. However, missing variable bias is undetected if both the changes in the dependent and explanatory variable are caused by a different, unobserved variable or shock. Some factors may be driving both patenting and employment growth. For example, Autor et al. (2020) show that exposure to import competition reduces businesses ability to invest in R&D, reducing patenting as a result. Earlier results already showed a negative effect on employment from the same trade shock (Autor et al., 2013).

Instrumental variables (IV) can be used to overcome this problem, but it is difficult to find instruments that are applicable in the different country contexts. For example, Lee and Clarke (2019) use the historical location of art and design schools to predict the current share of high-tech employment in the population. Given the different histories, such historical instruments would not be appropriate for the three countries studied here. The inclusion of lagged dependent variables can alleviate some of these concerns, as this controls for a general trend in the dependent variable that might at the same time affect the explanatory variable, such as a general improvement in the business environment of a region.

4. Results

Table 2 provides summary statistics for the estimation sample by country. The observations in this table are at the regional level. As explained above, Eurostat-based variables and patents are at the NUTS2 level, while ESS-derived variables are at the NUTS1 level and only available every other year. Overall, there are 96 NUTS2 regions, 21 in France, 38 in Germany and 37 in the UK. A small modification was made to the standard NUTS regions, by combining the five NUTS regions that make up Greater London into one. This is appropriate, as Greater London can be viewed as a single labour market area. Correspondingly, the Île de France region around Paris of a similar size to Greater London is a single NUTS2 region. There are 41 NUTS1 regions, 13 in France, 16 Germany and 12 in the UK.

The countries differ significantly in terms of patenting activity. There are on average 728 patent applications per NUTS2 region and year in Germany, but only 202 in the UK. French regions are in

Table 2
Summary statistics.

	Full sample		France		Germany		UK	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
NUTS2 level								
Patents	472	667	471	817	728	748	202	214
Graduate employment	309	321	395	471	277	172	290	322
Non-graduate employment	666	424	805	584	740	361	502	302
Total employment	986	721	1201	1036	1028	524	811	618
Population density	447	787	148	196	452	725	624	993
N	1749		399		694		656	
NUTS1 level								
Patents	1091	1709	912	1131	1583	2326	566	486
Graduate employment	777	581	834	592	651	588	903	533
Advanced vocational emp.	410	366	378	205	462	504	363	194
Total employment	2411	1687	2362	1189	2399	2243	2462	1017
Population density	569	1061	207	281	676	1041	694	1359
N	332		80		144		108	

Note: Observations are year x region. Variables at the NUTS2 level are for 2000–2019. Variables at the NUTS1 level for even numbered years between 2002 and 2018. All employment numbers are in thousands. Advanced vocational employment at the NUTS1 level is derived from ESS and normalised to total regional employment. Population density is measured in persons per square kilometre.

the middle, with 471 applications. However, the standard deviation is largest in France, suggesting a more unequal distribution. These differences are repeated at the NUTS1 level at a larger scale, given the higher aggregation of the data.

Regions differ slightly in average size across countries, so employment figures by educational attainment are not directly comparable. As a share of total employment, graduate employment is highest in the UK at 36% on average across NUTS2 regions (NUTS1: 37%), followed by France at 33% (NUTS1: 35%). The graduate employment share is markedly lower in Germany, at only 27% (NUTS1: 27%). In contrast, the share of employees with advanced vocational qualifications is higher in Germany, at 19% on average across NUTS1 regions, compared to 16% in France and 15% in the UK.

The detailed qualifications available on the ESS are self-reported and are less standardised than the graduate/ non-graduate definition. Table A.1 in the appendix provides summary statistics for different qualifications, utilising additional variables available on the ESS. This shows that in terms of income, years of education and other job characteristics, those with higher vocational qualifications fall neatly between those with only a secondary school diploma and a university degree.

Fig. 1 shows the average annual number of patent applications per 1000 employees at NUTS2 level. The rate of successful applications is highest in the south of Germany. This is in contrast to low levels of patenting in most regions in the east. In France, the rate of patenting is highest in the Île-de-France and Rhône-Alpes regions. As discussed above, patenting is overall lower in the UK, with the regions around Oxford and Cambridge having the highest rates of patenting. While London is performing well in absolute terms, the rate of patenting is low relative to total employment.

The next figures explore basic correlations between patenting and employment growth for different education groups. Fig. 2 plots average annual growth in non-graduate employment against total patenting over the observation period. The relationship is positive, if loose. The high-performing German regions of Oberbayern, Stuttgart and Düsseldorf, but also London, are close to the regression line. It should be stressed that these regions have highly successful, knowledge intensive economies overall, so that the correlation with patenting cannot be considered evidence of a causal relationship. On the other hand, the Île de France has seen among the highest rate of losses in non-graduate jobs. Overall, growth in non-graduate jobs is relatively low in France, both in highly innovative regions, such as Rhône-Alpes, as well as less innovative and more remote regions like Limousin. In the UK, some traditional manufacturing regions like the West Midlands experienced strong employment growth, despite being average in terms of innovativeness.

In contrast, Fig. 3 shows only a weak, negative unconditional correlation between patenting and graduate employment growth. While employment growth is on average higher for graduates than non-graduates, at around 3% against 0.1%, more innovative regions do not necessarily create more jobs. The following sections test for these relations formally.

4.1. Patenting and graduate employment

The first set of results looks at the interdependence of graduate employment and patenting. To visualise the results, Fig. 4 plots the β_h coefficients from Eq. (2). These are the coefficients of lagged patenting in a regression of changes in graduate employment over the time period indicated on the x-axis. Full regression results can be found in appendix Table A.2. As the estimation runs over changing time horizons, the y-axis can be interpreted as the difference in employment over the baseline in year t-1.

Fig. 4 shows a statistically significant increase in graduate employment in response to an increase in patenting. A 10% increase in patenting leads to an increase in graduate employment by 0.005%. Graduate employment then remains stable at the new higher level for several years. The employment response remains statistically significant for three years but then peters out, implying that employment reverts slowly back to the baseline. An intuitive interpretation of this result would be that inventions have a shelf-live, giving businesses a boost over several years, but continuous innovation is required to retain this advantage. Before year t-1, there is no statistically significant effect. This is the placebo test: changes in graduate employment in the past are not influenced by future patenting. This could be the case if some unobserved variable is driving both patenting and graduate employment. Reassuringly, this test suggests this is not the case.

Fig. 5 shows no evidence of a reverse effect of changes in graduate employment on patenting. Here, the dependent variable, the number of patents, is in log-levels and the y-axis can be interpreted as the number of additional patents filed between t−1 and the time horizon on the x-axis. Full regression results can be found in Table A.3 in the appendix. The point estimate hovers around zero and are statistically insignificant throughout. In this case, the significant and positive placebo effect is expected: patenting before a graduate employment shock is higher because patenting causes an increase in graduate employment as shown in Fig. 4. The causality runs clearly from innovation to graduate employment, not the other direction.

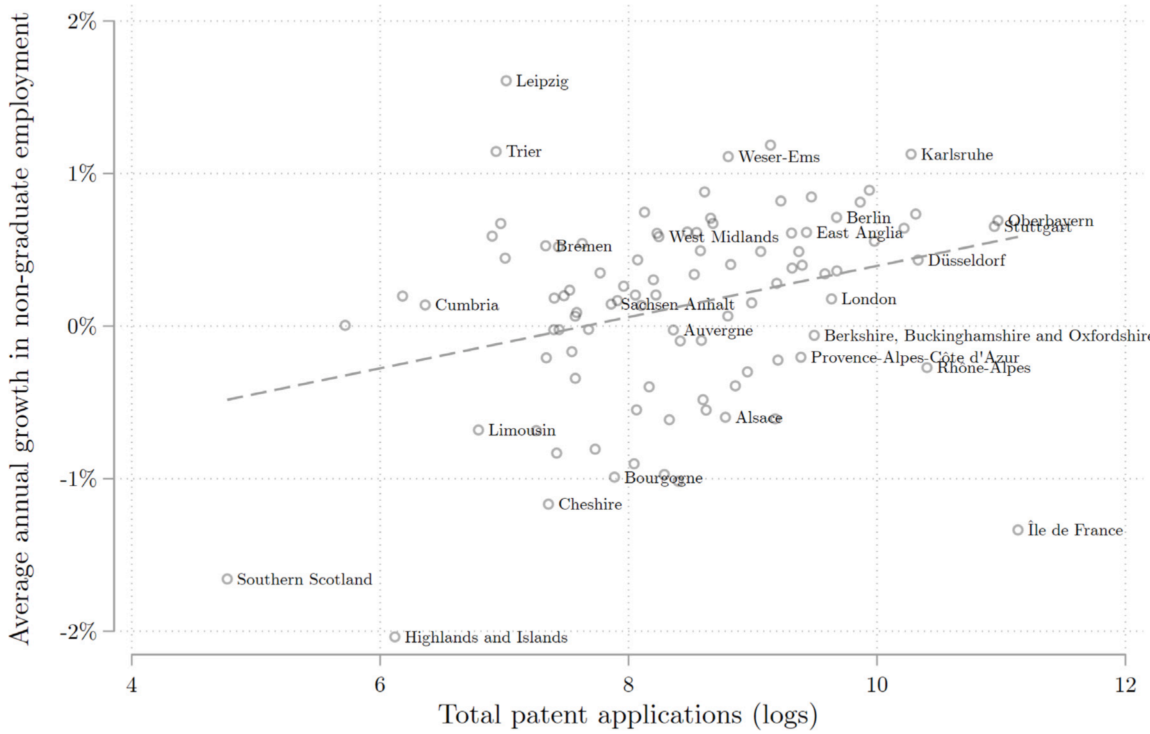

Fig. 2. Patenting and non-graduate employment growth.
Note: Total patent application for 2000–2018 and average annual employment growth for non-graduates for 2000–2019. Each observation is a NUTS 2 region.

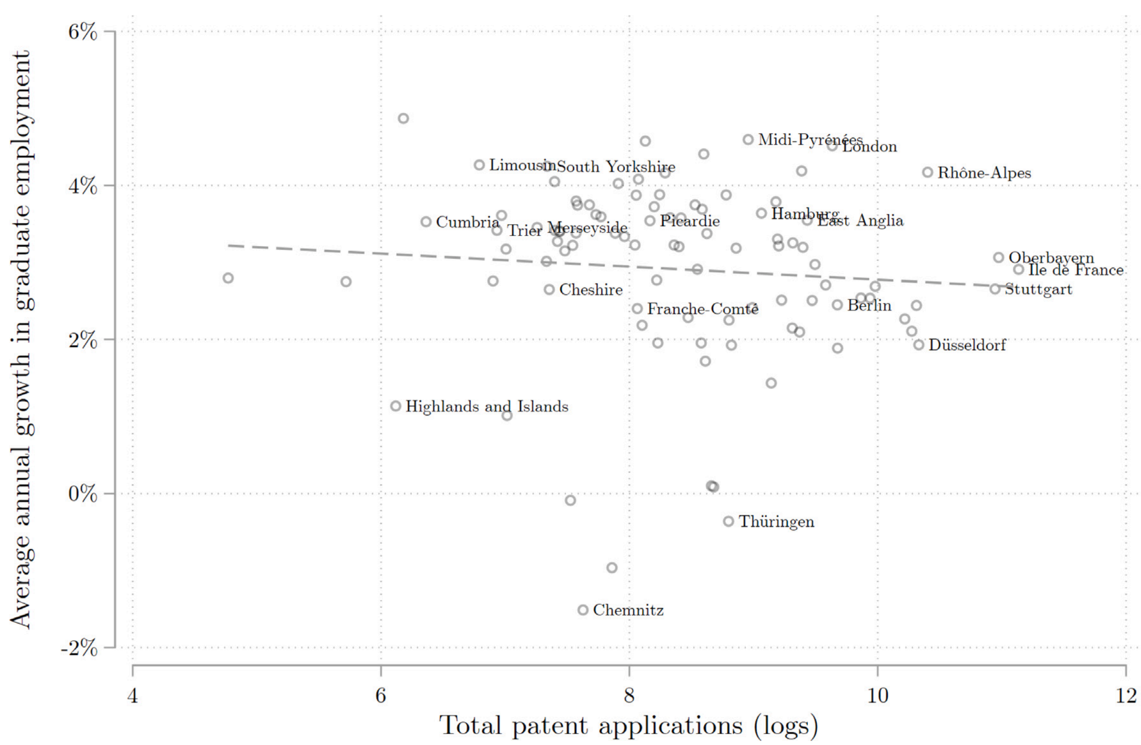

Fig. 3. Patenting and graduate employment growth.
Note: Total patent application for 2000–2018 and average annual employment growth for graduates for 2000–2019. Each observation is a NUTS 2 region.

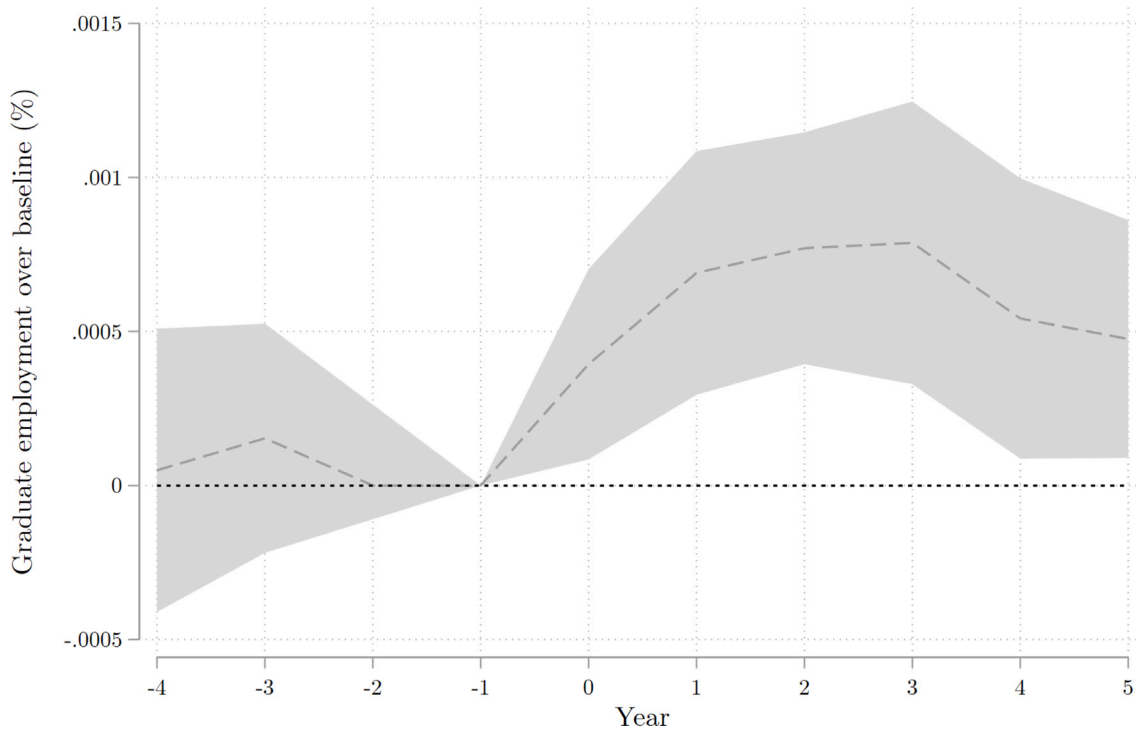

Fig. 4. Graduate employment response to change in patenting.
Note: Plot of β_hs from Eq. (2) against time horizon h. Baseline in t-1. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Table A.2.

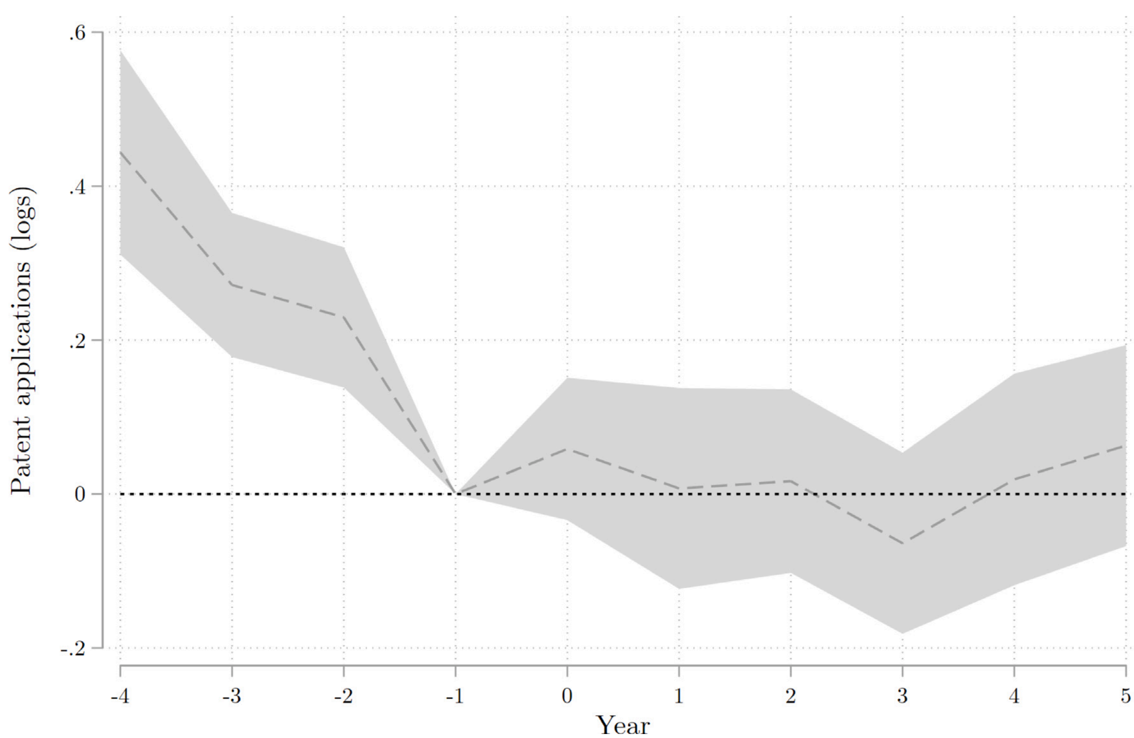

Fig. 5. Patenting response to change in graduate employment.
Note: Results from regression of patenting on lagged graduate employment. The plot shows the coefficients of graduate employment against time horizon h. Baseline in t-1. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Table A.3.

The results point to a positive effect of innovation on graduate employment, as found elsewhere in the literature. Note that there are several possible adjustment channels: the increase in employment could both indicate transitions from unemployment or outside the labour force, as well as in-migration of graduates, either from other regions or from abroad.

The significant effect from innovation on graduate employment but not in the other direction can be rationalised when considering that most graduates are unlikely to work in the innovative sector directly. Rather, the innovation creates a multiplier effect that creates further jobs in professional services that benefit indirectly from the innovation, such as legal and financial services (Moretti, 2012). This is not to say that graduates are not important for patenting, and more innovative regions are likely to have a higher share of graduate employment. However, growing graduate employment is not associated with a subsequent increase in patenting. This is in contrast to Faggian and McCann (2009) who find an effect of in-migration of graduates on patenting at the NUTS2 level in the UK. However, they consider recent graduates who migrate upon graduation only, which might constitute a more select group than the general population with a university degree.

4.2. Effects on workers without degree and intermediate qualifications

Next, I turn to the employment effects for those without a graduate degree. I estimate Eq. (3) by regressing the change in non-graduate employment on lagged graduate employment and patenting. The first set of results considers all non-graduates and the regressions are run at the NUTS2 regional level, while further results below consider workers with advanced vocational qualifications. As before, the effects shown in Figs. 6 and 7 can be understood as the change in non-graduate employment above the baseline in year t−1 in response to a 1% change in graduate employment or patenting, respectively. Full regression results can be found in Table A.4.

Fig. 6 shows a significant positive effect of graduate employment on non-graduate employment. Non-graduate employment remains around 0.1% above the baseline for two to three years after an initial 1% increase in graduate employment. The effect is temporary, however, and after four years non-graduate employment reverts back to the baseline. Reassuringly, there is no significant effect before year t-1, confirming that there is no evidence of unobserved variables driving employment growth across employment categories.

There is a small but short-lived effect of patenting on non-graduate employment, as Fig. 7 shows. Non-graduate employment is significantly above the baseline for two years after the patenting shock, but reverts back to the baseline by year t+2, with point estimates turning negative, albeit statistically insignificant.

The next set of results zooms in on workers with intermediate, advanced vocational qualifications that are below degree level. As explained above, data on mid-skilled employment is only available at two-year intervals and at the NUTS1 regional level, so that the effects shown in Figs. 8 and 9 have to be understood in terms of two-year compound growth rates. Full regression results can be found in Table A.5.

Fig. 8 shows the effect of graduate employment on mid-skilled employment. After two years, a 1% increase in graduate employment is estimated to lead to a 2% increase over the baseline in year t−2 in mid-skilled employment. This effect levels off slightly towards year t+6. The effects are larger in magnitude than the effect of graduate employment on all non-graduates shown in Fig. 6. A 1% increase in graduate employment is associated with a 2% increase in mid-skilled employment, compared to 0.1% for all non-graduates.

Fig. 9 shows the effect of patenting on mid-skilled employment. There is a statistically significant immediate positive effect, but employment reverts back to the baseline by year 4. However, the effect is much larger than that for all non-graduates, presented in Fig. 7.

Two results stand out from this analysis. First, non-graduate and mid-skilled employment respond positively both to changes in graduate employment and patenting. Second, the effects on mid-skilled employment are considerably larger than those for all graduates. While the effect of graduates on non-graduates is usually explained by the consumption of local services by high-paid workers (Lee and Clarke, 2019; Moretti, 2012), the larger effects for mid-skilled workers suggest that there may be complementarities with graduates driving the results. Furthermore, the direct effects from patenting suggest that workers with advanced qualifications below degree level can benefit directly from innovation, not just through the consumption channel from high-skilled workers.

4.3. Job-year multiplier calculation

In keeping with the literature, I calculate job multipliers from the coefficients estimated above (Moretti and Thulin, 2013; Lee and Clarke, 2019). Multiplier estimates are presented for each country separately, with underlying local projections estimates provided in the appendix, Figs. A.1 to A.3 and Tables A.6 to A.8.

To calculate impacts in terms of jobs created, the β_h coefficients, which can be interpreted as elasticities, are multiplied by the ratio of dependent to explanatory variable (Van Dijk, 2018). The multiplier for the effect of graduate employment on non-graduate employment is provided by Eq. (5), where $\overline{emp^{ng}}$ is average non-graduate employment and $\overline{emp^{g}}$ is average graduate employment per region and year in the estimation sample. Note that this is not the number of new jobs, but additional job-years over the estimation horizon between t and t+6. This calculation is more appropriate than a calculation of the number of jobs created, as some of the effects take time to materialise while others are only temporary and decline over time. A multiplier calculated for one point in time cannot reflect these dynamics.

$$M^{g,ng} = \sum_{i=1}^{h} \beta_h * \frac{\overline{EMP^{ng}}}{\overline{EMP^{g}}} \tag{5}$$

For the patenting coefficients, the calculation is slightly different, because patenting is measured as patents filed per year in logs. The coefficient is approximately equal to the predicted change in the employment growth rate, but needs to be divided by 100, as Eq. (6) shows.

$$M^{pat,ng} = \sum_{i=1}^{h} \frac{\beta_h}{100} * \frac{\overline{EMP^{ng}}}{\overline{PAT}} \tag{6}$$

Multiplier estimates for the whole sample as well as by country are provided in Table 3. Note that these estimates are noisy, combining several point estimates, some of which are statistically insignificant and dependent on employment estimates derived from surveys.

Across the three countries, a patent is estimated to create 2.2 graduate job-years, e.g. 2.2 jobs for one year, or 1.1 jobs that remain for two years. Across NUTS2 regions, an average of 472 patents are filed per year. By a back-of-the-envelope calculation, patenting can account for 208 additional jobs, or 0.07% of total graduate employment.[1] While this overall effect is small, there is substantial variation across countries. The effect of graduate jobs per patent is largest in Germany, at 1.78 job-years per patent. This translates into 259 additional graduate jobs on average per year and NUTS2 region, representing 0.1% of total graduate employment. The effect in France is slightly smaller, at 1.6 job-years (150 job-years or 0.04% total graduate employment). The estimate for the UK is negative, at −1.47. However, all underlying point estimates for the UK are statistically insignificant, implying that the effect is overall close to zero. Estimates of the effect of patenting in the UK and France are in part noisier than those for Germany, as patenting is overall lower, and has less variation (in France outside the two innovation hubs of the Île-de-France and Rhône-Alpes).

[1] This is calculated as job-year multiplier divided by 5 to annualise the effect, and multiply by the average number of patents per year and region.

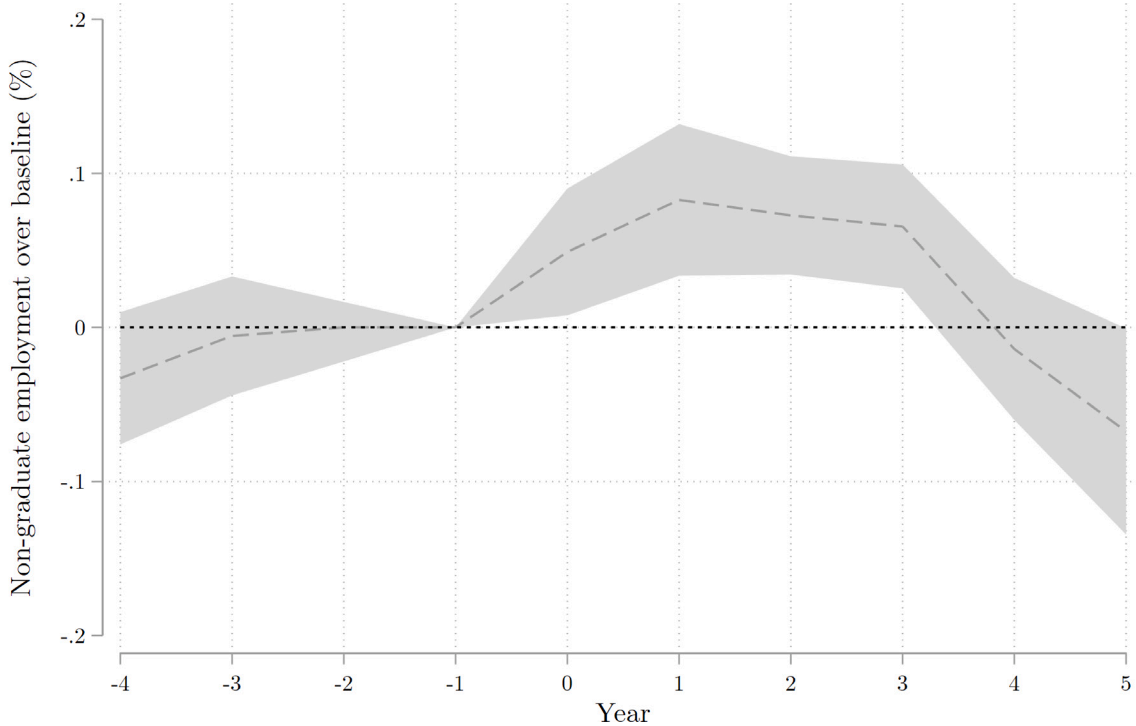

Fig. 6. Non-graduate employment response to change in graduate employment.
Note: Plot of β_h^gs from Eq. (3) against time horizon h. Baseline in t-1. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Table A.4.

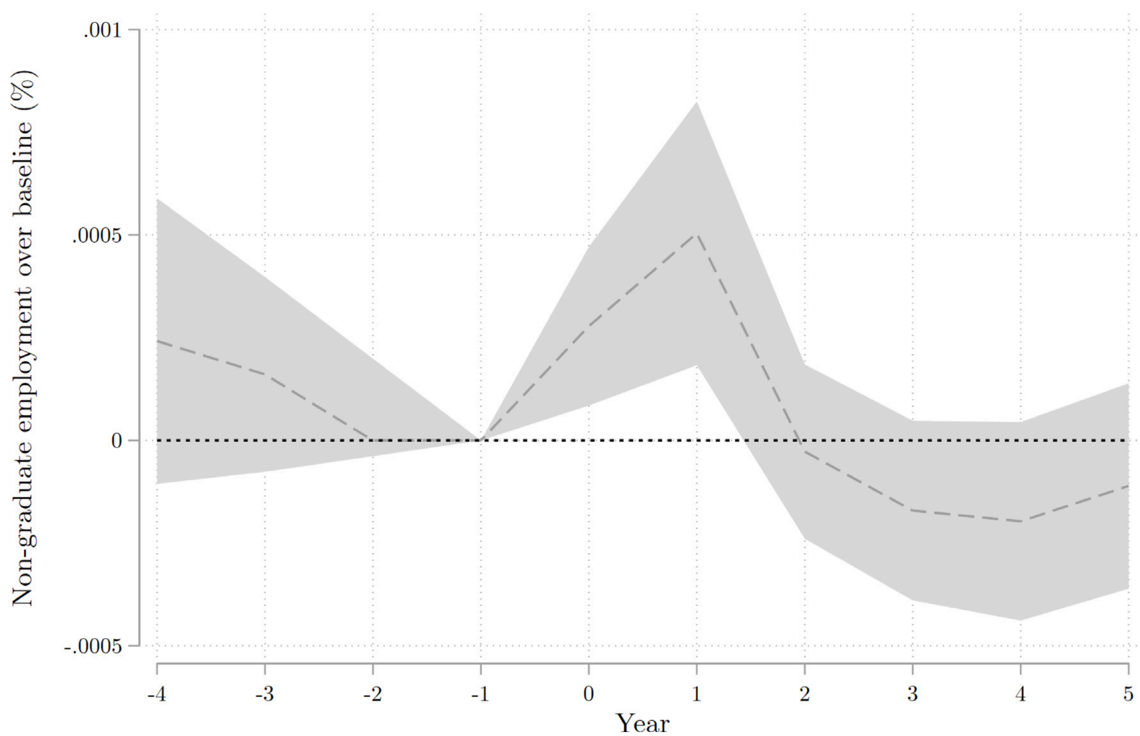

Fig. 7. Non-graduate employment response to change in patenting.
Note: Plot of β_h^ps from Eq. (3) against time horizon h. Baseline in t-1. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Table A.4.

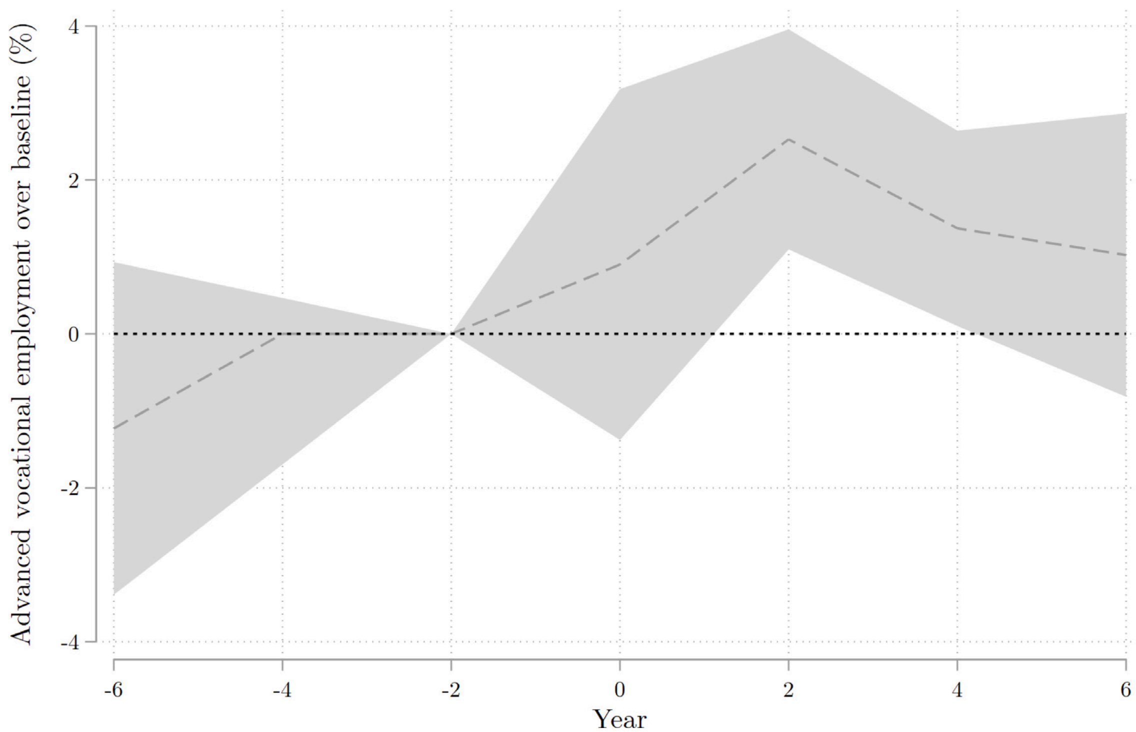

Fig. 8. Advanced vocational employment response to graduate change in employment.
Note: Plot of β_h^ps from Eq. (4) against time horizon h. Baseline in t-2. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Table A.5.

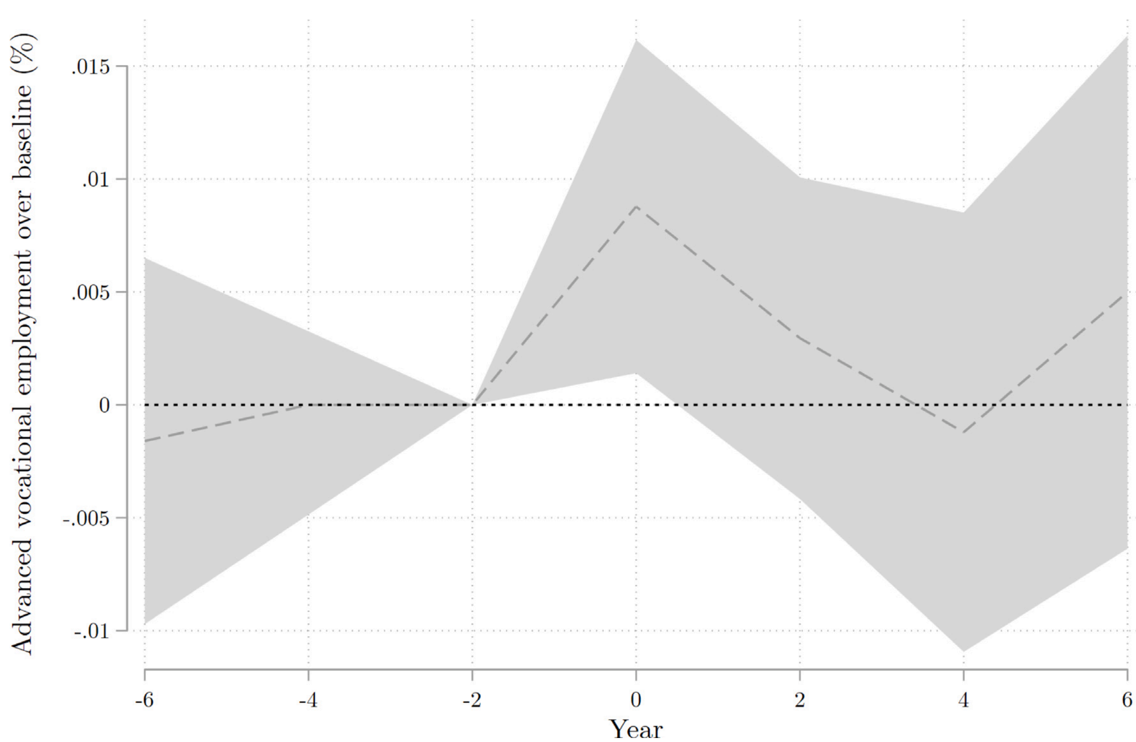

Fig. 9. Advanced vocational employment response to change in patenting.
Note: Plot of β_h^ps from Eq. (4) against time horizon h. Baseline in t-2. 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Table A.5.

Table 3
Job-year multipliers.

	All	France	Germany	UK
Graduate job-years per patent	2.20	1.60	1.78	−1.47
Non-graduate job-years per graduate job	0.35	0.034	1.09	−0.046
Non-graduate job-years per patent	0.90	−0.35	2.49	1.21
Higher vocational job-years per graduate job	2.42	3.84	−0.19	3.13
Higher vocational job-years per patent	5.62	14.2	3.54	18.2

Note: Multipliers derived from beta coefficients depicted in Figs. 4 to 9 and Figs. A.1 to A.3. Multipliers can be interpreted as additional job-years created due to an additional job/ patent over a five year horizon.

Looking at the effects for non-graduate jobs, the overall multiplier is 0.35 job-years per graduate job for the whole sample. This is an economically meaningful number, corresponding to 22,000 jobs on average per year and NUTS2 region, or 5% of total non-graduate employment. By country, the effect is largest in Germany at 1.09 job-years per graduate job (60,386 jobs per NUTS2 region, or a share of 8%). The effects for France and the UK are close to zero, corresponding to insignificant point estimates throughout. These estimates are comparable to those found in the literature. Lee and Clarke (2019) estimate the effect for a single point in time over a 6-year period. However, the employment groups considered are different, as they consider the effect of high-tech on non-tradable employment. Their preferred specification yields a multiplier of 0.6. For comparison, the estimates in Table 3 should be divided by 5 to arrive at an annualised effect. They are therefore considerably smaller than Lee and Clarke (2019)'s effects, ranging from 0.0028 for Germany to 0.122 for the combined sample. The latter effect is similar to OLS estimates by Lee and Clarke (2019). Moretti and Thulin (2013) consider 10-year intervals for the US and 6-year intervals for Sweden for the effect of tradable on non-tradable employment. Their preferred estimates for the effects of tradable employment on non-tradable unskilled are 0.3 for the US and between −0.27 and 0.51 for Sweden. This last estimate is most similar to estimates arrived at here. It should be noted though that the tradable jobs are a smaller subset of overall employment than graduate employment. It is therefore not surprising that the magnitudes of effects are somewhat different.

The patent multiplier for non-graduates is smaller than that for graduates, at 0.9 job-years per patent, corresponding to the small and partly insignificant point estimates seen in Fig. 7. This corresponds to 85 jobs on average per NUTS2 region, or 0.01% of non-graduate employment. The effects from patenting on non-graduates is largest in Germany, at 2.49 job years per patent (363 jobs per NUTS2 region, or 0.05% of total non-graduate employment), derived from point estimates that are statistically significant from year 0 to 3. The estimated multiplier for France is negative but small, at −0.35, and based on overall insignificant point estimates. While the multiplier for the UK is relatively large, at 1.21, this is also based on insignificant point estimates.

The multiplier effects for mid-skilled, or vocational employment are larger in magnitude, in particular the patent multiplier. The overall multiplier predicts 2.42 mid-skilled jobs to be created for every graduate job, corresponding to 376,068 jobs on average per year at the NUTS1 level, or 91% of mid-skilled employment. The patent multiplier is estimated at 5.62 mid-skilled jobs per patent, corresponding to 1226 jobs and 0.05% of total mid-skilled employment.

At the country level, the estimated multipliers are more difficult to interpret, as many of the underlying point estimates are statistically insignificant. This is also driven by small sample sizes, as these estimates rely on a smaller number of regions at a higher level of aggregation, and a shorter time series. For France, both multipliers are based on point estimates that are statistically significant at the beginning of the estimation period but then turn insignificant. The estimates predict 3.84 additional mid-skilled jobs per graduate job (166,800 jobs, 44% of total mid-skilled employment) and 14.2 additional mid-skilled jobs per patent (2590 jobs, 0.6% of total mid-skilled employment). The estimated multipliers are similar for the UK, at 3.13 mid-skilled job per graduate job, and 18.2 mid-skilled jobs per patent. However, the patent multiplier is based on statistically insignificant point estimates throughout. The large magnitude of the multiplier may be explained by overall very low levels of patenting in many regions. The multipliers for mid-skilled employment for Germany are difficult to interpret due to the volatility of the underlying point estimates. The graduate employment is small and negative, but this masks significant positive point estimates in the middle of the estimation period, while those at the beginning and end are negative but statistically insignificant. Similarly, the point estimates for the patent multiplier hover around zero.

The results are suggestive of differences in the effects across the three countries. Some of these differences can be rationalised by what we know about the countries innovation and education systems, as well as industry specialisations. The response of non-graduate employment to a patenting shock is larger in Germany, possibly because commercialising a successful innovation may lead to increased production in the large domestic manufacturing sector. Given the relatively low levels of patenting in most regions in the UK, it is unsurprising to find no significant effects from patenting in the UK. Mid-skilled employment in the UK does not move much, as the UK system of vocational training is relatively weak compared to France and Germany. The small response from non-graduate employment is surprising given the UKs flexible labour market regime. The UK has generally lower unemployment rates than either France or Germany, approaching full employment towards the end of the study period. Adjustments in the labour market may therefore take place more through moving between jobs, rather than through transitions from unemployment.

4.4. Robustness checks

In the following, I present several robustness checks on the specifications of the main variables used in the analysis. First, I restrict patent applications to patents exhibiting novelty. The International Patent Classification (IPC) which defines technologies, is updated in response to radically new inventions that do not fit in any of the existing categories. I use this feature to define novel patents as being filed in a technology class that was first introduced no more than 10 years ago at the time of priority filing. As most patents are filed in multiple classes, any patent filed in at least one novel class is considered novel. By this definition, around 16% of patents in the sample are considered novel. Novel patents are important, because they may be the economically most disruptive, introducing radically new technologies. However, these technologies may yet be relatively far away from commercialisation and the economic value of novel patents may be relatively more uncertain than incremental changes to established technologies.

Local projection results including only novel patents in the analysis are presented in Fig. A.4 in the appendix. Graduate employment shows no response to changes in these types of patents. The point estimate even briefly turns negative and statistically significant in year t+4, before returning to the baseline. In contrast, non-graduate employment does show a positive response, but this takes longer to materialise and is of a smaller magnitude than the main specification. There is no statistically significant response from mid-skilled employment.

Another way to isolate the most important inventions is by considering only cited patents. Inventors are required to cite technologies that their patent relies on. As a consequence, citations are a good indicator of a patent's value (Hall et al., 2005). However, the distribution of citations is highly skewed (Gandal et al., 2021): many patents are never cited, while a small number of patents receive thousands of citations. Recently approved patents tend to have few or no citations just because they had no time yet to accumulate any. As a simple delineation, I consider only patents that have been cited at least once, which reduces the average number of patents per region in the sample by 60%.

Results for estimations using this subsample of patents are presented in Fig. A.5 in the appendix. The results are somewhat surprising. There is a negative response of graduate employment to cited patents. In contrast, the response of non-graduate employment is significant, with a similar magnitude and dynamic profile as in the main specification. Likewise, the response of mid-skilled employment is significant, positive and increasing over time. Note that patents are still counted at the time of filing, they are only considered cited if they will eventually be cited by 2023, where the dataset ends. Therefore, the observed correlations cannot be explained by the timing of citations.

As another robustness check, I consider different categorisations of employment. Classifying workers by their formal qualifications does not take into account experience, informal learning on the job and soft skills. Workers may work in positions that they are – in terms of their qualifications or skill set – over or under-qualified for. Different categorisations may therefore be along the lines of industries, in particular high- versus low-tech industries, and occupations.

First, I examine the relation between patenting and employment in high-tech and low-tech sectors, where high-tech is defined according to the Eurostat definition, including high-technology manufacturing and knowledge-intensive high-technology services and low-tech is defined as low and medium-low-technology manufacturing and less knowledge-intensive services. Data are made available by Eurostat at the NUTS 2 regional level from 2008 to 2019. Due to the shorter time series available, local projects analysis is repeated only for periods $t-1$ to $t+4$. Results are presented in Fig. A.6 in the appendix, showing no statistically significant response of high-tech employment to patenting and from low-tech employment to either patenting or high-tech employment, with the exception of a significant effect of low-tech employment in response to high-tech employment and a small negative effect of patenting on high-tech employment at the end of the estimation period. That suggests that the effects observed above occur through a wide range of industries not only in particularly technically advanced sectors.

Next, I consider employment effects for employees in professional and technical and associate professionals (henceforth "technical employment"). These figures are available from Eurostat at the NUTS1 regional level from 2008 to 2019. I repeat the local projections estimation for the response of employment in professional occupations to patenting, and of employment in technical occupations to professional employment and patenting. Results are presented in Fig. A.7 in the appendix. There is a small negative but temporary response of professional employment to patenting, and a small immediate but temporary response of technical employment to professional employment. The channel from patenting to technical employment is statistically insignificant for the whole observation period.

5. Conclusion

The paper considered employment multiplier effects from patenting and graduate employment on workers without graduate education and workers with vocational qualifications. There are three principle results that provide lessons to policy makers. First, the results confirm a significant multiplier effect from graduate employment and patenting on both groups of non-graduate employees, but effects are larger for those with vocational qualifications. Second, the effects are temporary, with employment reverting back to the baseline after several years. Third, the effects vary by country, pointing to the importance of underlying institutions.

The positive effect of patenting on non-graduate employment, even if short-lived, shows that not all innovation may be labour-displacing at the regional level. As expected, the magnitude of the effect is larger for workers with advanced vocational qualifications. This suggests that innovative firms and industries may to some extend halt or slow down the decline in employment of some mid-skilled occupations. As vocational skills are likely to be more industry and firm specific, this points to the importance of considering innovation and skills policy together, both at the national as well as at the local level. While recent policy, for example in the UK, has aimed to expand access to higher education, the results suggest that investment in vocational training would make innovation more inclusive.

The local projections method shows that considering these effects over several years, instead of a single point in time is important. The effects of patenting on graduate employment, and the effect of graduate on non-graduate employment mid-skilled employment rise over two to three years and then decline again. In contrast, the effects of patenting on non-graduate and mid-skilled employment are relatively short-lived, and employment reverts back to the baseline after a short, positive impact. This is an important qualification to previous research, which only considered multiplier effects for a single point in time.

Further research can unpack the differences across countries, in particular by comparing a wider set of countries, or by studying the effects of institutional arrangements over time. Research into the adjustment channels can reveal whether some labour market institutions are more conducive to making use of technological opportunities, not only by providing a flexible labour force, but also incentivising investments in the skills required. This may require the use of microdata that includes information on individuals' career trajectories. While these datasets cannot generally be integrated across countries, richer individual data would also allow a more detailed study of skill groups beyond the categories available from the ESS, as well as taking into account industry- and plant-specific experience. This would further allow studying the interaction between skills and occupations. Indeed, occupations may capture important aspects of tacit, informal skills that formal qualifications may not capture, and may also approximate the quality of employment.

CRediT authorship contribution statement

Carolin Ioramashvili: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The replication package for this paper is available at the following address: https://doi.org/10.5255/UKDA-SN-857246.

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Appendix

See Tables A.1–A.8 and Figs. A.1–A.7.

Table A.1
Descriptives for educational categories in ESS.

	Higher vocational		No degree		Degree		Advanced degree	
	Mean/SD	N	Mean/SD	N	Mean/SD	N	Mean/SD	N
Gross pay	10,681.5 (23,575.1)	859	7097.4 (18,936.4)	3405	18,312.1 (30,266.3)	1196	17,931.5 (34,124.4)	466
Househ income decile	6.79 (2.38)	4915	6.07 (2.50)	18,114	7.62 (2.29)	7796	7.69 (2.33)	3557
Years of education	14.9 (2.61)	5683	12.8 (2.69)	21,276	17.4 (3.14)	9141	18.4 (3.07)	3936
Working hours	40.8 (12.4)	5632	38.6 (13.1)	21,055	41.3 (12.4)	9040	42.3 (12.3)	3890
Job requires >basic edu	0.79 (0.41)	1023	0.59 (0.49)	4136	0.90 (0.30)	1447	0.92 (0.27)	557
Job requires learning	2.99 (0.95)	1030	2.65 (1.04)	4200	3.16 (0.88)	1453	3.11 (0.87)	557
Has partner	0.68 (0.47)	5704	0.66 (0.48)	21,385	0.67 (0.47)	9181	0.69 (0.46)	3957
N	5704		21,385		9181		3957	

Note: ESS rounds 1-9 (2002–2018) for France, Germany and the UK. Includes information on respondents only. Gross pay only available for round 2 (2004). "No degree" excludes those with higher vocational qualification. Household income decile only available for rounds 4-9 (2008–2018). Dummy variable asking whether current job requires more than basic education only available for rounds 2 and 5 (2004 and 2010). Variable asking whether job requires learning new things (coded 1 = Not at all true to 4 = Very true) only available for rounds 2 and 5 (2004 and 2010). Years of education and working hours available for all rounds. Partner is also available for all rounds and indicates whether respondent has a partner for whom employment and educational attainment are also available.

Table A.2
Graduate employment response to change in patenting.

	t−4	t−3	t	t+1	t+2	t+3	t+4	t+5
L.Log patents	0.0049 (0.023)	0.015 (0.019)	0.039** (0.016)	0.069*** (0.020)	0.077*** (0.019)	0.079*** (0.023)	0.054** (0.023)	0.048** (0.019)
L.Log grad. emp.	−0.69*** (0.037)	−0.87*** (0.041)	−0.34*** (0.035)	−0.56*** (0.039)	−0.65*** (0.028)	−0.67*** (0.032)	−0.68*** (0.051)	−0.73*** (0.046)
L2.Log grad. emp.	0.34*** (0.039)	0.64*** (0.034)	0.14*** (0.036)	0.28*** (0.037)	0.27*** (0.046)	0.22*** (0.036)	0.20*** (0.036)	0.23*** (0.035)
Log pop density	1.49*** (0.22)	0.89*** (0.14)	0.33* (0.18)	0.54** (0.25)	1.11*** (0.25)	1.43*** (0.24)	1.59*** (0.24)	1.64*** (0.23)
Recession (2009–2010)	0.0048 (0.0057)	−0.0021 (0.0054)	0.016*** (0.0047)	0.017** (0.0068)	0.027*** (0.0062)	0.035*** (0.0062)	0.013** (0.0052)	−0.0043 (0.0054)
Constant	−6.26*** (1.12)	−3.69*** (0.71)	−0.86 (0.88)	−1.74 (1.26)	−4.29*** (1.22)	−5.59*** (1.16)	−6.17*** (1.16)	−6.27*** (1.11)
Observations	892	892	892	892	892	892	892	892
within R^2	0.33	0.44	0.15	0.25	0.35	0.42	0.44	0.51
between R^2	0.0063	0.0069	0.0014	0.0037	0.0024	0.0041	0.013	0.018
overall R^2	0.0028	0.0043	0.0027	0.0044	0.0032	0.0043	0.0094	0.015
F-statistic	80.1	115.4	27.6	42.3	127.3	98.2	38.5	56.4
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses.
Note: The top row shows the estimation horizon. The dependent variable is graduate employment growth over the estimation horizon, e.g. between t−4 and t−1 in the first column and between t+5 and t−1 in the last column. t−1 and t−2 not estimated due to multicollinearity. Estimation at the NUTS 2 region level. Region fixed effects included in all specifications.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

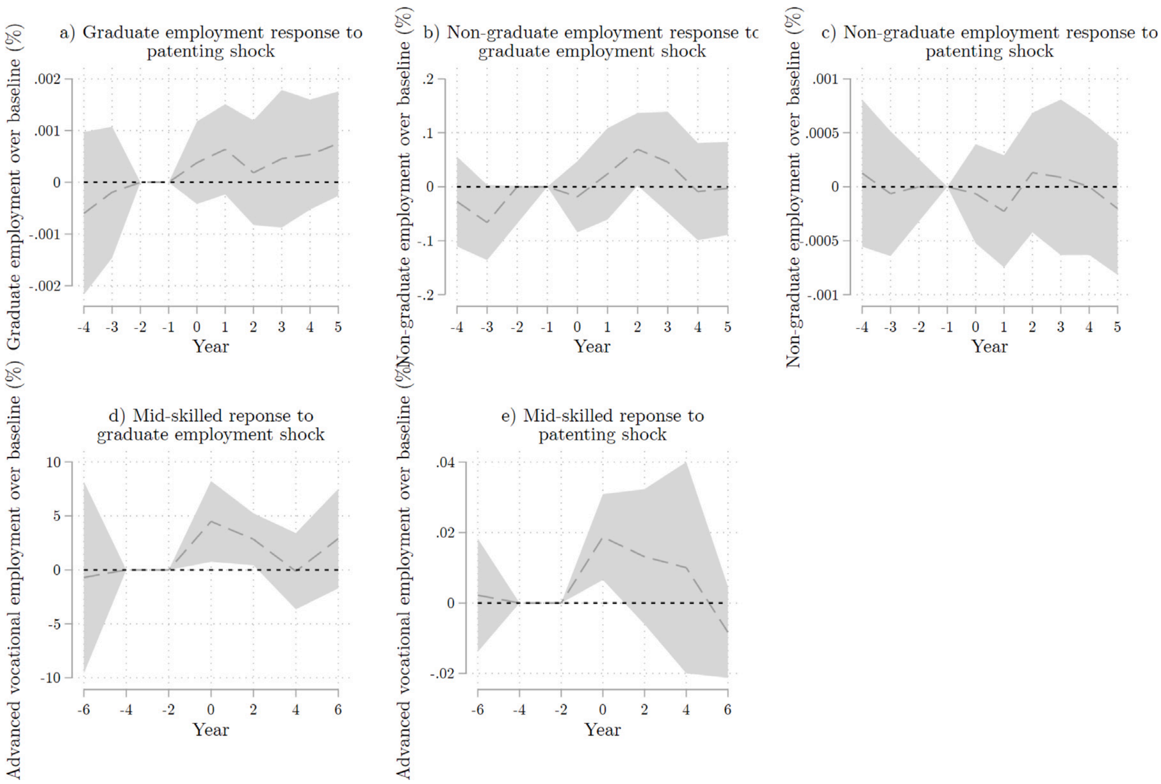

Fig. A.1. Estimations for France.
Note: Plot of β coefficients from Eqs. (2)–(4) including French regions only. Baseline in t−1 for figure (a)–(c) and in t−2 for (d) and (e). 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Tables A.6–A.8.

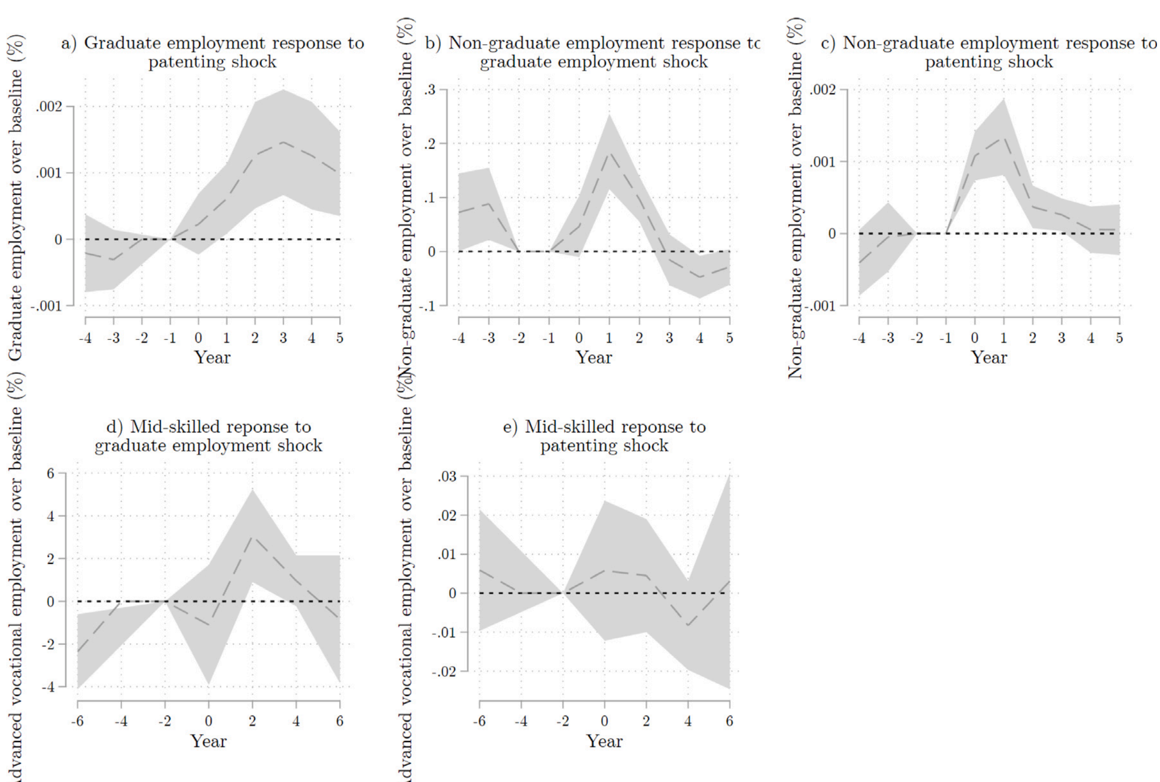

Fig. A.2. Estimations for Germany.
Note: Plot of β coefficients from Eqs. (2)–(4) including German regions only. Baseline in t−1 for figure (a)–(c) and in t−2 for (d) and (e). 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Tables A.6–A.8.

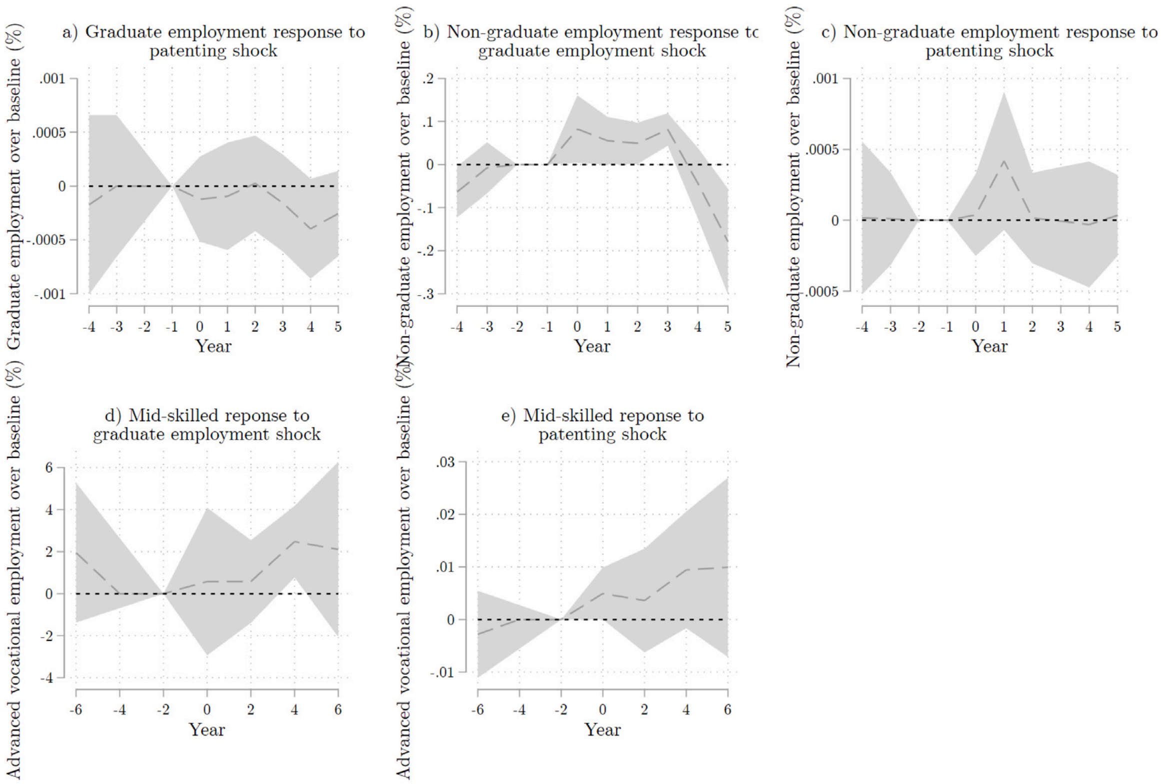

Fig. A.3. Estimations for the UK.
Note: Plot of β coefficients from Eqs. (2)–(4) including UK regions only. Baseline in t−1 for figure (a)–(c) and in t−2 for (d) and (e). 95% confidence intervals shaded in grey around point estimates. Full regression results can be found in Tables A.6–A.8.

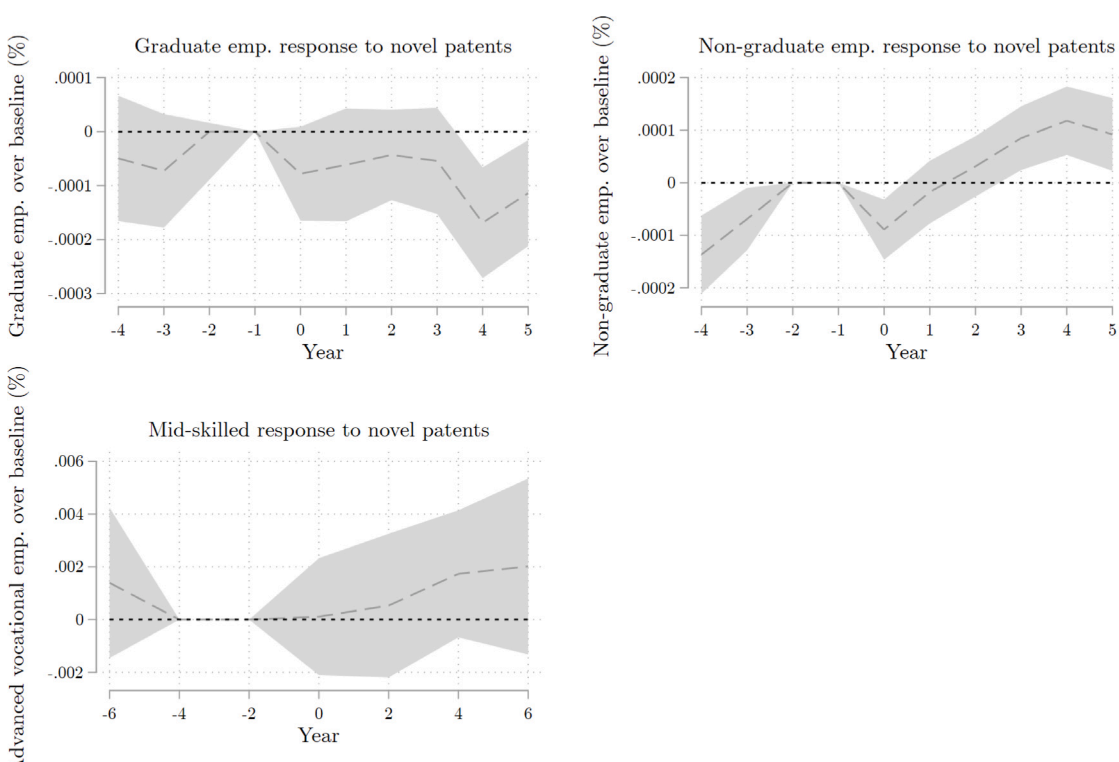

Fig. A.4. Employment responses to novel patents.
Note: Local projects for the response of graduate, non-graduate and advanced vocational employment to novel patents. Novel patents are defined as falling into a technology class that was introduced no more than ten years ago at the time of priority application. 95% confidence intervals shaded in grey around point estimates.

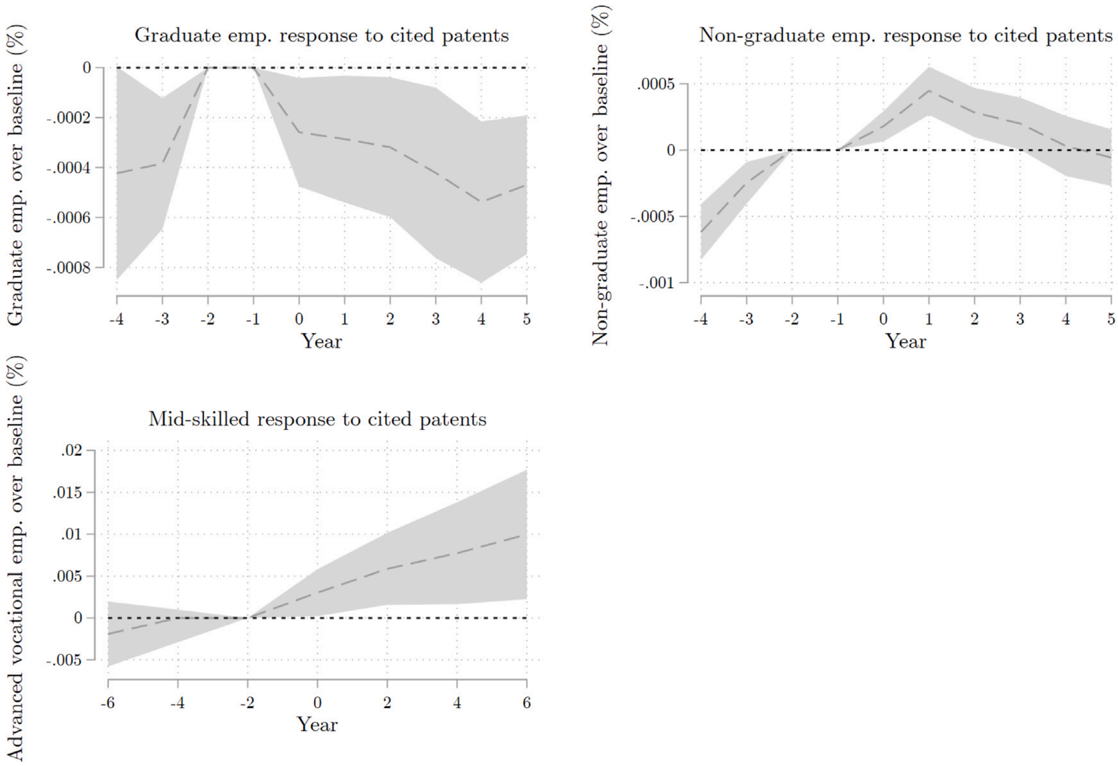

Fig. A.5. Employment responses to cited patents.
Note: Local projects for the response of graduate, non-graduate and advanced vocational employment to cited patents. Cited patents are those that have received at least one citation. 95% confidence intervals shaded in grey around point estimates.

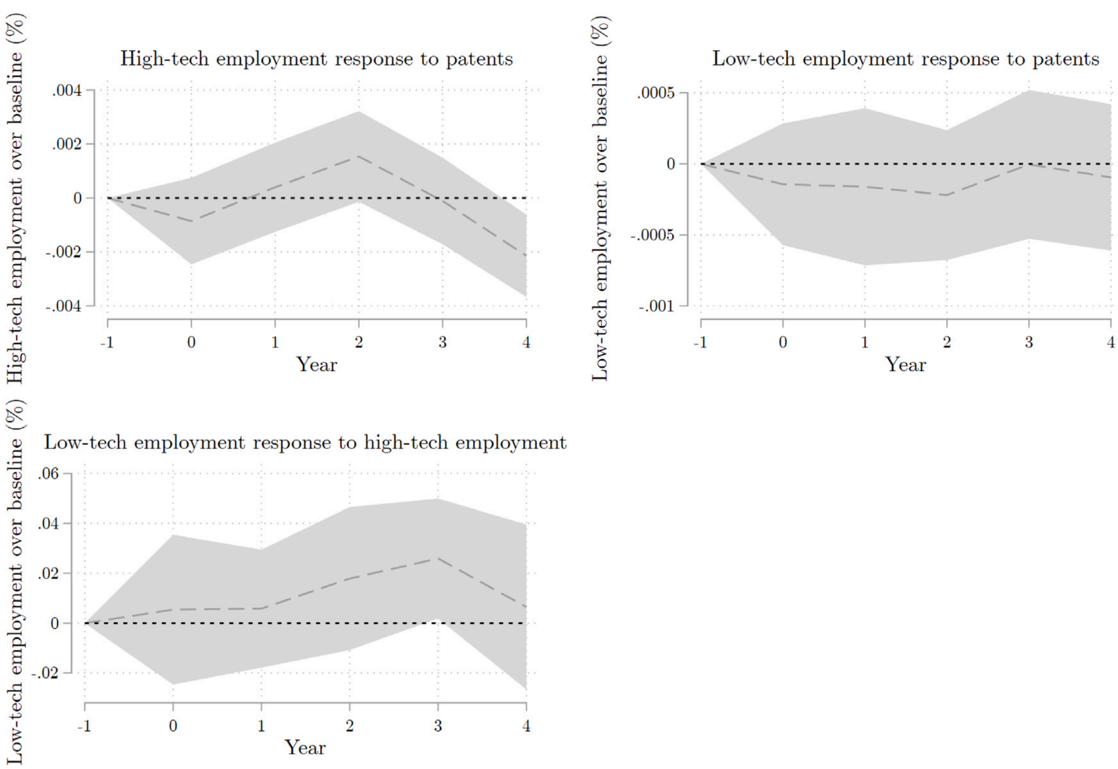

Fig. A.6. Employment in high- and low-tech industries.
Note: Local projects for the response of high-tech employment to patenting and low-tech employment to patenting and high-tech employment at the NUTS2 level. 95% confidence intervals shaded in grey around point estimates.

Table A.3
Patenting response to change in graduate employment.

	t−4	t−3	t−2	t	t+1	t+2	t+3	t+4	t+5
L.Log patents	0.21***	0.35***	0.39***	0.34***	0.28***	0.16***	0.16***	0.12**	0.051
	(0.073)	(0.044)	(0.058)	(0.057)	(0.049)	(0.051)	(0.051)	(0.048)	(0.043)
L.Log grad. emp.	0.44***	0.27***	0.23***	0.058	0.0073	0.017	−0.064	0.019	0.063
	(0.067)	(0.047)	(0.046)	(0.047)	(0.066)	(0.060)	(0.059)	(0.069)	(0.066)
Log pop density	−0.92*	−0.92**	−0.68*	−0.031	0.33	0.76*	1.17***	0.91**	0.58
	(0.55)	(0.44)	(0.37)	(0.37)	(0.37)	(0.41)	(0.42)	(0.41)	(0.41)
Recession (2009–2010)	0.054***	0.083***	0.044***	−0.0060	0.0098	−0.0077	0.0014	0.020	0.017
	(0.011)	(0.013)	(0.012)	(0.0088)	(0.010)	(0.010)	(0.011)	(0.013)	(0.012)
Constant	6.95**	7.12***	5.84***	3.60*	2.27	0.56	−1.23	0.0091	1.89
	(2.91)	(2.43)	(2.04)	(2.01)	(2.01)	(2.24)	(2.27)	(2.21)	(2.17)
Observations	892	892	892	892	892	892	892	892	892
within R^2	0.20	0.25	0.23	0.14	0.095	0.045	0.048	0.042	0.025
between R^2	0.012	0.034	0.16	0.99	0.61	0.25	0.17	0.18	0.18
overall R^2	0.0099	0.031	0.16	0.97	0.61	0.26	0.18	0.19	0.19
F-statistic	20.3	38.8	25.0	11.0	10.1	3.5	4.2	3.5	1.8
P of model test	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.14

Standard errors in parentheses.
Note: The top row shows the estimation horizon. The dependent variable is patenting growth over the estimation horizon, e.g. between t−4 and t−1 in the first column and between t+5 and t−1 in the last column. t−1 not estimated due to multicollinearity. Estimation at the NUTS 2 region level. Region fixed effects included in all specifications.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.4
Non-graduate employment response to changes in employment and patenting.

	t−4	t−3	t−2	t	t+1	t+2	t+3	t+4
L.Log patents	0.024	0.016	0.028***	0.050***	−0.0027	−0.017	−0.020	−0.011
	(0.018)	(0.012)	(0.0098)	(0.016)	(0.011)	(0.011)	(0.012)	(0.013)
L. Δ log grad. emp.	−0.033	−0.0055	0.049**	0.083***	0.073***	0.066***	−0.014	−0.068**
	(0.022)	(0.019)	(0.021)	(0.025)	(0.019)	(0.020)	(0.023)	(0.034)
L.Log non-grad emp.	−1.18***	−1.14***	−0.44***	−0.78***	−0.97***	−0.95***	−1.12***	−1.11***
	(0.032)	(0.034)	(0.044)	(0.049)	(0.060)	(0.033)	(0.050)	(0.052)
L2.Log non-grad emp.	0.27***	0.58***	−0.11***	−0.19***	−0.10**	−0.12***	0.014	0.073
	(0.044)	(0.039)	(0.035)	(0.038)	(0.044)	(0.037)	(0.041)	(0.057)
Log pop density	0.68***	0.31**	−0.58***	−1.14***	−1.27***	−1.22***	−1.21***	−1.09***
	(0.18)	(0.13)	(0.073)	(0.13)	(0.15)	(0.14)	(0.14)	(0.14)
Recession (2009–2010)	0.029***	0.020***	−0.011***	−0.0061	−0.012***	−0.019***	−0.014***	−0.0045
	(0.0043)	(0.0023)	(0.0028)	(0.0044)	(0.0039)	(0.0037)	(0.0040)	(0.0042)
Constant	1.95*	1.78**	6.44***	12.0***	13.7***	13.5***	13.7***	12.6***
	(1.01)	(0.70)	(0.50)	(0.76)	(0.80)	(0.79)	(0.81)	(0.73)
Observations	892	892	892	892	892	892	892	892
within R^2	0.55	0.57	0.34	0.60	0.70	0.71	0.70	0.66
between R^2	0.0075	0.0069	0.0070	0.062	0.050	0.046	0.047	0.053
overall R^2	0.0041	0.011	0.00010	0.0024	0.0056	0.0094	0.013	0.020
F-statistic	340.4	284.9	96.6	116.9	209.5	349.1	143.1	169.4
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses.
Note: The top row shows the estimation horizon. The dependent variable is non-graduate employment growth over the estimation horizon, e.g. between t−4 and t−1 in the first column and between t+5 and t−1 in the last column. t−1 not estimated due to multicollinearity. Estimation at the NUTS 2 region level. Region fixed effects included in all specifications.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.5
Advanced vocational employment response to changes in employment and patenting.

	t−6	t	t+2	t+4	t+6
L.Log patents 2y.	−0.16	0.88**	0.30	−0.12	0.50
	(0.41)	(0.37)	(0.36)	(0.49)	(0.57)
L2. Δ log grad. emp.	−1.23	0.90	2.53***	1.37**	1.02
	(1.09)	(1.15)	(0.72)	(0.64)	(0.93)
L2. Δ log mid-skilled emp	−0.47***	−0.48***	−0.48***	−0.52***	−0.43***
	(0.078)	(0.056)	(0.059)	(0.049)	(0.066)
Log pop density	1.62	1.18	2.22	4.52*	4.09
	(1.92)	(0.94)	(1.58)	(2.68)	(2.92)
Recession (2009–2010)	0.093	0.20*	0.057	0.0036	0.014
	(0.15)	(0.11)	(0.11)	(0.088)	(0.086)
Constant	−8.01	−12.8**	−14.3*	−24.2	−26.3
	(11.3)	(4.74)	(8.47)	(14.6)	(16.4)
Observations	209	249	209	169	131
within R^2	0.21	0.29	0.40	0.48	0.37
between R^2	0.019	0.027	0.036	0.024	0.0057
overall R^2	0.0094	0.010	0.0098	0.00081	0.000092
F-statistic	11.7	21.0	36.8	31.3	11.8
P of model test	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses.
Note: The top row shows the estimation horizon. Consistent with data availability, the estimation horizon increases in steps of two years. The dependent variable is advanced vocational employment growth over the estimation horizon, e.g. between t−6 and t−2 in the first column and between t+6 and t−2 in the last column. t−2 and t−4 not estimated due to multicollinearity. Vocational employment is normalised by total employment. Log patent applications include all applications in last two years. Estimation at the NUTS 1 region level. Region fixed effects included in all specifications.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

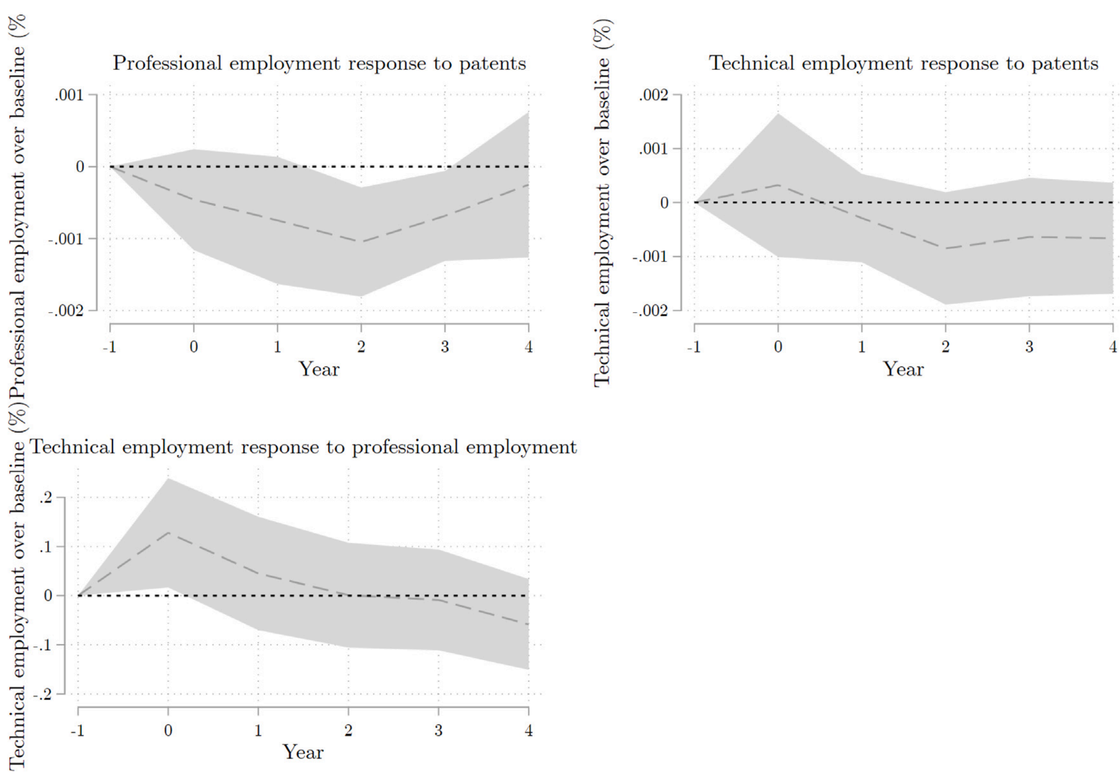

Fig. A.7. Employment in professional and technical occupations.
Note: Local projects for the response of employment in professional occupations to patenting and technical occupations to patenting and professional occupations at the NUTS1 level. 95% confidence intervals shaded in grey around point estimates.

Table A.6
Graduate employment response to changes in patenting by country.

	t−4	t−3	t−2	t	t+1	t+2	t+3	t+4
France								
L.Log patents	−0.060	−0.019	0.038	0.064	0.019	0.046	0.054	0.075
	(0.079)	(0.064)	(0.040)	(0.044)	(0.051)	(0.067)	(0.054)	(0.051)
L.Log grad. emp.	−0.80***	−0.98***	−0.42***	−0.74***	−0.80***	−0.83***	−0.82***	−0.88***
	(0.074)	(0.074)	(0.083)	(0.069)	(0.062)	(0.080)	(0.11)	(0.087)
L2.Log grad. emp.	0.37***	0.68***	0.021	0.16**	0.14*	0.15**	0.11	0.098
	(0.098)	(0.071)	(0.065)	(0.068)	(0.071)	(0.065)	(0.070)	(0.064)
Log pop density	3.29***	2.12***	1.82***	2.71***	3.37***	3.27***	3.21***	3.21***
	(0.84)	(0.48)	(0.64)	(0.75)	(0.73)	(0.70)	(0.58)	(0.54)
Constant	−12.6***	−8.10***	−6.40**	−9.65***	−11.9***	−11.5***	−11.1***	−10.7***
	(3.14)	(1.78)	(2.67)	(3.11)	(2.88)	(2.74)	(2.35)	(2.24)
Observations	210	210	210	210	210	210	210	210
within R^2	0.32	0.46	0.22	0.37	0.48	0.52	0.54	0.60
between R^2	0.078	0.055	0.14	0.14	0.12	0.11	0.097	0.086
overall R^2	0.0091	0.0065	0.0015	0.0024	0.0050	0.0075	0.0087	0.0087
F-statistic	43.4	50.6	19.3	38.9	59.3	31.0	17.1	31.7
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Germany								
L.Log patents	−0.021	−0.031	0.023	0.061**	0.13***	0.15***	0.13***	0.098***
	(0.030)	(0.023)	(0.023)	(0.027)	(0.040)	(0.040)	(0.041)	(0.032)
L.Log grad. emp.	−0.68***	−0.81***	−0.29***	−0.40***	−0.63***	−0.50***	−0.59***	−0.74***
	(0.063)	(0.068)	(0.045)	(0.047)	(0.048)	(0.047)	(0.039)	(0.053)
L2.Log grad. emp.	0.26***	0.56***	0.15***	0.21***	0.32***	0.086	0.091	0.24***
	(0.069)	(0.069)	(0.056)	(0.053)	(0.068)	(0.073)	(0.067)	(0.056)
Log pop density	0.31	−0.039	−0.69***	−0.72***	−0.075	0.49	0.48	0.61*
	(0.28)	(0.19)	(0.16)	(0.26)	(0.29)	(0.36)	(0.36)	(0.32)
Constant	0.57	1.72	4.47***	4.72***	1.41	−1.31	−0.68	−1.17
	(1.63)	(1.14)	(1.00)	(1.57)	(1.79)	(2.19)	(2.17)	(1.89)
Observations	354	354	354	354	354	354	354	354
within R^2	0.47	0.48	0.14	0.19	0.31	0.36	0.44	0.56
between R^2	0.12	0.00015	0.037	0.010	0.17	0.20	0.25	0.22
overall R^2	0.0029	0.023	0.0034	0.0015	0.093	0.12	0.18	0.19
F-statistic	41.9	62.7	18.4	20.8	67.8	57.1	70.7	54.3
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
UK								
L.Log patents	−0.017	0.00013	−0.012	−0.0095	0.0026	−0.016	−0.040*	−0.026
	(0.042)	(0.033)	(0.020)	(0.025)	(0.022)	(0.023)	(0.023)	(0.020)
L.Log grad. emp.	−0.80***	−1.03***	−0.61***	−0.94***	−0.89***	−0.96***	−0.96***	−0.92***
	(0.10)	(0.088)	(0.063)	(0.069)	(0.064)	(0.073)	(0.12)	(0.099)
L2.Log grad. emp.	0.19**	0.51***	0.011	0.14*	0.11	0.14*	0.13**	0.16***
	(0.071)	(0.052)	(0.061)	(0.074)	(0.089)	(0.075)	(0.060)	(0.051)
Log pop density	2.86***	2.48***	2.93***	3.90***	4.00***	4.10***	4.04***	3.50***
	(0.70)	(0.48)	(0.31)	(0.53)	(0.61)	(0.66)	(0.62)	(0.35)
Constant	−13.2***	−11.5***	−13.5***	−18.0***	−18.7***	−18.9***	−18.4***	−15.7***
	(3.35)	(2.32)	(1.49)	(2.66)	(2.97)	(3.08)	(2.81)	(1.66)
Observations	328	328	328	328	328	328	328	328
within R^2	0.32	0.49	0.35	0.52	0.55	0.61	0.61	0.57
between R^2	0.0018	0.027	0.0066	0.0061	0.020	0.065	0.15	0.17
overall R^2	0.00065	0.0021	0.00035	0.0028	0.0048	0.0088	0.020	0.031
F-statistic	30.5	45.0	35.4	46.4	50.1	84.7	19.8	35.1
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses.
Note: The top row shows the estimation horizon. The dependent variable is graduate employment growth over the estimation horizon, e.g. between t−4 and t−1 in the first column and between t+5 and t−1 in the last column. t−1 and t−2 not estimated due to multicollinearity. Estimation at the NUTS 2 region level. Region fixed effects included in all specifications.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Table A.7
Effects on non-graduate employment by country.

	t−4	t−3	t−2	t	t+1	t+2	t+3	t+4
France								
L.Log patents	0.013	−0.0064	−0.0065	−0.023	0.013	0.0088	0.000038	−0.020
	(0.034)	(0.029)	(0.023)	(0.026)	(0.028)	(0.036)	(0.032)	(0.031)
L. Δ log grad. emp.	−0.027	−0.066*	−0.019	0.024	0.070*	0.046	−0.0090	−0.0029
	(0.042)	(0.035)	(0.033)	(0.043)	(0.034)	(0.047)	(0.045)	(0.044)
L.Log non-grad emp.	−1.18***	−1.22***	−0.52***	−0.70***	−0.78***	−0.61***	−0.59***	−0.72***
	(0.070)	(0.078)	(0.087)	(0.099)	(0.088)	(0.084)	(0.083)	(0.100)
L2.Log non-grad emp.	0.14	0.56***	−0.079	0.029	0.20**	0.15*	0.0037	−0.029
	(0.098)	(0.071)	(0.082)	(0.088)	(0.075)	(0.076)	(0.095)	(0.094)
Log pop density	1.10**	0.51**	−0.52*	−0.85***	−1.55***	−1.85***	−1.99***	−1.83***
	(0.40)	(0.23)	(0.25)	(0.28)	(0.31)	(0.32)	(0.38)	(0.40)
Constant	1.65	2.02*	6.38***	8.45***	10.9***	11.6***	13.0***	13.4***
	(1.85)	(1.08)	(1.44)	(1.33)	(1.34)	(1.43)	(1.97)	(2.17)
Observations	210	210	210	210	210	210	210	210
within R^2	0.58	0.60	0.33	0.38	0.45	0.46	0.49	0.51
between R^2	0.21	0.12	0.012	0.049	0.034	0.030	0.018	0.011
overall R^2	0.042	0.044	0.00000021	0.0014	0.0017	0.0025	0.0017	0.00086
F-statistic	85.1	66.5	16.0	19.3	39.9	43.1	20.8	16.6
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Germany								
L.Log patents	−0.041*	−0.0047	0.11***	0.13***	0.037**	0.026**	0.0054	0.0052
	(0.023)	(0.024)	(0.017)	(0.027)	(0.015)	(0.011)	(0.016)	(0.018)
L. Δ log grad. emp.	0.073*	0.088**	0.046	0.19***	0.097***	−0.015	−0.047**	−0.028*
	(0.036)	(0.034)	(0.029)	(0.035)	(0.021)	(0.024)	(0.020)	(0.017)
L.Log non-grad emp.	−1.10***	−1.22***	−0.30***	−0.71***	−1.00***	−1.25***	−1.22***	−1.03***
	(0.063)	(0.052)	(0.049)	(0.043)	(0.034)	(0.044)	(0.045)	(0.042)
L2.Log non-grad emp.	0.21***	0.68***	−0.27***	−0.32***	−0.22***	0.066*	0.24***	0.27***
	(0.054)	(0.051)	(0.049)	(0.038)	(0.034)	(0.034)	(0.030)	(0.029)
Log pop density	−1.35***	−0.82***	−0.097	−0.047	−0.30**	−0.31*	−0.35	−0.42*
	(0.19)	(0.11)	(0.095)	(0.11)	(0.12)	(0.18)	(0.22)	(0.25)
Constant	13.6***	8.08***	3.58***	6.13***	9.38***	9.25***	8.29***	7.28***
	(1.19)	(0.74)	(0.66)	(0.79)	(0.77)	(1.06)	(1.25)	(1.40)
Observations	354	354	354	354	354	354	354	354
within R^2	0.54	0.63	0.36	0.63	0.84	0.86	0.78	0.69
between R^2	0.028	0.020	0.0031	0.050	0.0000012	0.0075	0.016	0.0098
overall R^2	0.00021	0.000056	0.0034	0.0026	0.0023	0.0033	0.0043	0.0021
F-statistic	110.3	215.0	53.3	104.9	262.1	232.0	178.2	171.7
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
UK								
L.Log patents	0.0016	0.0011	0.0038	0.042*	0.0016	−0.00057	−0.0030	0.0035
	(0.027)	(0.016)	(0.015)	(0.025)	(0.016)	(0.019)	(0.022)	(0.014)
L. Δ log grad. emp.	−0.064**	−0.0074	0.082**	0.055*	0.049**	0.082***	−0.043	−0.18***
	(0.030)	(0.030)	(0.040)	(0.028)	(0.024)	(0.019)	(0.041)	(0.062)
L.Log non-grad emp.	−1.12***	−1.02***	−0.52***	−0.87***	−1.04***	−0.96***	−1.29***	−1.33***
	(0.041)	(0.035)	(0.059)	(0.058)	(0.092)	(0.040)	(0.061)	(0.053)
L2.Log non-grad emp.	0.19**	0.43***	−0.024	−0.099*	−0.048	−0.28***	−0.11	−0.034
	(0.074)	(0.048)	(0.049)	(0.056)	(0.060)	(0.042)	(0.066)	(0.097)
Log pop density	1.90***	1.20***	−0.91***	−1.80***	−1.92***	−1.52***	−1.26***	−0.85***
	(0.18)	(0.12)	(0.090)	(0.16)	(0.17)	(0.16)	(0.19)	(0.21)
Constant	−5.23***	−3.31***	8.57***	16.0***	17.6***	16.3***	15.7***	13.1***
	(0.98)	(0.68)	(0.53)	(0.86)	(1.04)	(0.98)	(1.16)	(0.94)

(*continued on next page*)

Table A.7 (*continued*).

	t−4	t−3	t−2	t	t+1	t+2	t+3	t+4
Observations	328	328	328	328	328	328	328	328
within R^2	0.70	0.62	0.41	0.76	0.79	0.81	0.82	0.80
between R^2	0.0013	0.0094	0.0016	0.037	0.029	0.031	0.045	0.072
overall R^2	0.0017	0.0042	0.00067	0.00031	0.00021	0.00031	0.00051	0.0017
F-statistic	325.2	278.9	83.1	114.3	103.9	249.8	397.4	426.9
P of model test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses.

Note: The top row shows the estimation horizon. The dependent variable is non-graduate employment growth over the estimation horizon, e.g. between t−4 and t−1 in the first column and between t+5 and t−1 in the last column. t−1 not estimated due to multicollinearity. Estimation at the NUTS 2 region level. Region fixed effects included in all specifications.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Table A.8
Effects on advanced vocational employment by country.

	t−6	t	t+2	t+4	t+6
France					
L.Log patents 2y.	0.22	1.87**	1.31	1.00	−0.83
	(0.81)	(0.61)	(0.97)	(1.51)	(0.65)
L2. Δ log grad. emp.	−0.70	4.50**	2.84**	−0.12	2.91
	(4.49)	(1.89)	(1.21)	(1.78)	(2.33)
L2. Δ log mid-skilled emp	−0.67***	−0.62***	−0.66***	−0.70***	−0.62***
	(0.21)	(0.087)	(0.095)	(0.15)	(0.066)
Log pop density	−3.76	4.74	−0.78	3.14	15.0*
	(7.40)	(2.75)	(3.19)	(7.71)	(5.54)
Recession (2009–2010)	0.93*	0.84***	0.56	0.47*	0.43**
	(0.45)	(0.18)	(0.34)	(0.24)	(0.096)
Constant	16.9	−37.3**	−5.92	−23.1	−70.3**
	(37.7)	(12.3)	(10.8)	(30.5)	(23.6)
Observations	44	56	44	32	20
within R^2	0.45	0.60	0.59	0.74	0.84
between R^2	0.18	0.0014	0.18	0.0032	0.10
overall R^2	0.00015	0.0057	0.21	0.0032	0.00048
F-statistic	5.8	21.8	22.9	.	.
P of model test	0.01	0.00	0.00	.	.
Germany					
L.Log patents 2y.	0.59	0.58	0.45	−0.83	0.31
	(0.79)	(0.91)	(0.73)	(0.58)	(1.40)
L2. Δ log grad. emp.	−2.36**	−1.10	3.07**	0.96	−0.84
	(0.89)	(1.42)	(1.10)	(0.60)	(1.51)
L2. Δ log mid-skilled emp	−0.54***	−0.38***	−0.43***	−0.50***	−0.29**
	(0.10)	(0.078)	(0.11)	(0.051)	(0.13)
Log pop density	4.13*	2.91*	7.38***	12.6***	9.52**
	(2.15)	(1.51)	(1.78)	(2.42)	(4.21)
Recession (2009–2010)	0.070	0.22	−0.074	−0.15	−0.027
	(0.18)	(0.15)	(0.18)	(0.12)	(0.16)
Constant	−28.1*	−20.8***	−45.3***	−65.5***	−56.2*
	(14.6)	(6.56)	(10.9)	(14.7)	(28.9)
Observations	93	109	93	77	63
within R^2	0.34	0.21	0.46	0.62	0.27
between R^2	0.030	0.016	0.024	0.017	0.0079
overall R^2	0.013	0.0037	0.00030	0.0071	0.0023
F-statistic	15.2	13.3	90.2	73.3	2.1
P of model test	0.00	0.00	0.00	0.00	0.12
UK					
L.Log patents 2y.	−0.28	0.49*	0.36	0.94	0.99
	(0.42)	(0.25)	(0.50)	(0.56)	(0.86)
L2. Δ log grad. emp.	1.95	0.58	0.58	2.47**	2.10
	(1.68)	(1.77)	(0.99)	(0.86)	(2.10)
L2. Δ log mid-skilled emp	−0.25**	−0.57***	−0.43***	−0.49***	−0.50***
	(0.11)	(0.088)	(0.041)	(0.095)	(0.11)

(*continued on next page*)

Table A.8 (*continued*).

	t−6	t	t+2	t+4	t+6
Log pop density	−1.60	−1.02	−3.55***	−2.75	−2.75
	(2.16)	(1.40)	(1.13)	(1.71)	(2.17)
Recession (2009–2010)	−0.17	−0.014	−0.097	0.12	0.12
	(0.18)	(0.21)	(0.12)	(0.15)	(0.15)
Constant	11.0	2.63	18.3***	9.60	9.38
	(10.5)	(8.34)	(5.12)	(11.1)	(16.3)
Observations	72	84	72	60	48
within R^2	0.16	0.41	0.43	0.52	0.60
between R^2	0.16	0.00000032	0.0069	0.020	0.018
overall R^2	0.0021	0.049	0.0014	0.0020	0.023
F-statistic	4.0	26.1	36.6	24.3	12.5
P of model test	0.03	0.00	0.00	0.00	0.00

Standard errors in parentheses.
Note: The top row shows the estimation horizon. Consistent with data availability, the estimation horizon increases in steps of two years. The dependent variable is advanced vocational employment growth over the estimation horizon, e.g. between t−6 and t−2 in the first column and between t+6 and t−2 in the last column. t−2 and t−4 not estimated due to multicollinearity. Vocational employment is normalised by total employment. Log patent applications include all applications in last two years. Estimation at the NUTS 1 region level. Region fixed effects included in all specifications.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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