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Employment and Technological Change: On the Geography of Labour Market Adjustments

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Abstract
This paper investigates the impact of technological change on local labour market outcomes in Britain. Using a newly assembled panel database for the period 2000-2007 and a directly observed measure of technological change based on patent records, the analysis suggests that employment levels are relatively lower in places that are more exposed to technological shocks depending on their existing industrial specialization. Results also suggest that the magnitude of the impact varies across locations and typologies of workers. The negative impact on employment is particularly evident in areas characterized by weaker agglomeration economies and specialization in mature industries and for intermediate skilled individuals employed in "routinary" activities.

Keywords: Local labour market, employment, technological change, skills
JEL Classifications: R12; R23; R21; O33; J24

1. *Introduction*

The investigation of the link between employment and technological change has been one of the most controversial and popular issues within the economics literature. No consensus has been reached so far on the magnitude and sign of the relation and recent evidence suggests the emergence of heterogeneous territorial responses to shifts in technological trajectories. Places such as Liverpool and Detroit, for example, were centres of excellence due to their strategically located harbour on the one hand and global leadership in the car industry on the other. However, the evolution of technology, which reduced transport costs and routinized car production, lowered their competitive advantage and started their long lasting decline. Liverpool has lost thousands of jobs over less than two decades while Detroit is still the most cited example of a declining city.

Interestingly, other areas in the same countries, despite being subject to similar changes, were less affected or more able to put in place adequate adjustment mechanisms to keep climbing the innovation ladder. Recent research shows that places that have been able to make the transition towards high-tech sectors, and been able to exploit the opportunities associated with these technological changes, are also those which show the best economic performance (Moretti 2012).

Researchers have long speculated about the reasons behind this evidence and more recently they have started to acknowledge that, by failing to account for the spatial dimension of labour markets, relevant aspects of the adjustment mechanisms at play are missed (Moretti 2008; Autor et al, 2013). This paper contributes to the ongoing debate on the link between employment and technological change by building upon this recent research while widening the spectrum of analysis. In fact, the bulk of these existing contributions, while accounting more accurately for the spatial scale of labour markets, also rely on a specific measure of technological change (i.e. computerization) and on a given labour market outcome (i.e. job polarization). A wider investigation of the impact of aggregate technological shifts on local employment outcomes, therefore, remains an empirically important issue to complement existing evidence with more generalizable findings.

The analysis focuses on Britain as an interesting case due to the significant degree of segmentation (in terms of both geography and industries) of its labour market, with increasing disparities between local areas and little evidence to suggest nationwide adjustment mechanisms have been effective (Turok and Edge, 1999). Notwithstanding the focus of this study, it is hoped that more general conclusions, especially with respect to industrialized economies, can be drawn.

To measure technological change, the paper employs a directly observed and widely used proxy of technology, based on patent data. Patents have been traditionally considered a relevant indicator for measuring innovation and technical change (Basberg 1987; Hagedoorn and Cloodt 2003) and they have been extensively exploited in previous contributions looking at the impact of technological change on employment (Coad and Rao 2011; Greenhalgh et al. 2001; Van Reenen 1997 among others)[2] as well as in studies investigating the determinants of innovative

[2] The majority of existing studies looking at the impact of technological change on employment outcomes adopt either a country level or a micro perspective. Despite not accounting explicitly for the spatial scale of the labour market, they provide support for the adoption of patents data as a possible proxy for technological change. Aggregate studies have generally adopted R&D measures due to their availability at country level (Simonetti et al. 2000; Tancioni and Simonetti 2002; Bogliacino and Vivarelli 2011). However, the nonlinear relation between inputs and outputs of the process has generated concerns about the reliability of

activities (Hunt and Gauthier-Loiselle 2010; Peri 2012 among others). They represent a reliable proxy for "a stock of blueprint technologies that can be actualized in the form of an innovation outcome when economic conditions are favorable" (Van Reenen 1997, p.263), providing a more generalizable measure of technological change when compared to measures of computerization. The measure is constructed using records from the US Patent Office - USPTO (rather than European Patent Office - EPO - or UK Patent Office) in order to exploit their greater representativeness of international technological trends and their stronger exogeneity with respect to the British labour market and sectorial dynamics.

This empirical investigation makes use of a reduced form approach where the measure of technology based on patents is related to a range of employment outcomes. To model the impact of shifts in technological trajectories (interpreted as observable time trend component), the paper exploits the insights from the econometric literature on common shocks (Andrews 2005, Bai 2009). Local labour markets are treated as sub-units that are heterogeneously exposed to

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such measures. Micro level investigations have tried to overcome this limitation by exploiting more direct measures of innovative performance, either patent data or innovation surveys. Among studies adopting patents data, Van Reenen (1997), analyzing manufacturing firms' in Britain, found a positive impact of technological change on employment and Blanchflower and Burgess (1999) found support for this evidence looking at two different panels of British and Australian firms. Greenhalgh et al (2001) found a positive impact for R&D, patents and trademarks on employment for a panel of British production firms and Coad and Rao (2011), looking at US manufacturing firms, found a positive impact on employment. Bogliacino et al (2012) confirmed the same finding for a panel of European manufacturing and service firms in the high technology sector and Gagliardi et al (2014) found a positive employment effect of innovation in green sectors. Among recent studies exploiting innovation surveys, Harrison et al (2008) found that the prevalence of either a displacement or a compensation effect at firm level depends on the typology of innovation performed (product or process). Following similar reasoning, Hall et al. (2008) suggested the lack of a significant displacement effect for process innovation and a moderate employment growth due to product innovation.

technological changes depending on their initial industry specialization. This is a key difference with respect to existing studies that attribute the differential effect of computerization trends on the basis of the historical skill composition (as in Beaudry et al. 2010) or occupational mix (as in Autor and Dorn, 2013). In fact, while it is reasonable to assume that these dimensions may drive territorial responses in terms of adjustments across the skill/job task distribution (i.e. places with a greater share of employment in "routinary activities" and intermediate skills pay the greatest cost in terms of polarization of the workforce), a more comprehensive analysis needs to acknowledge that regional variation in the industrial structure is the primary source of heterogeneity in territorial responses to changes in technological trajectories (Autor et al, 2013).

The findings from this study suggest that the impact of technological change is negatively correlated to employment outcomes in Britain and that employment levels are relatively lower in places that are more exposed to technological shocks relative to those that are less exposed depending on their initial industrial specialization. This evidence is particularly significant for areas characterized by weaker agglomeration economies and specialization in mature industries, where job losses due to shifts in technological trajectories remain persistent over time. Intermediate skilled individuals are those paying the greatest cost in term of employment outcomes. These findings contribute to the generalization of the job market polarization hypothesis by employing a wider measure of technological change with respect to "computerization". Coherent with the existing literature, in fact, this study finds that the impact of technological change on employment is dependent on the extent to which different typologies of jobs are more or less technology-intensive. This evidence explains why middle-skilled occupations have declined with respect to both higher and low skilled occupations (Spitz-Oener

2006; Autor, Katz, and Kearney 2006; Goos and Manning 2007; Goos, Manning, and Salomons 2009; Dustmann et al, 2009, Michaels, Natray, and Van Reenen 2010; Autor and Dorn 2013). It also provides support for the so called "extreme skills complementarity hypothesis" (Eeckhout 2014), which suggests that places that are able to attract skilled workers are also those providing better job opportunities for less qualified people. High skilled workers tend, in fact, to generate increasing demand for low skilled services, generating more intense compensating mechanisms within each labour market across sectors and skill groups.

To support the reliability of the findings of this study, the paper deals with several identification threats. First, the impact of technological shocks is attributed to each local labour market area on the basis of the pre-existing industrial structure, which allows for the exogeneity conditions of the traditional Bartik (1993) instrumental variable approach to be included. This precaution also rules out the concern that the adoption of a measure of technological change based on US patents may impact on the number of UK firms in operation each year due to increasing competition in specific sectors experiencing greater technological progress overseas (i.e. the effect attributed to technological change also accounts for variations in the share of local firms by sectors and its impact in each labour market area due to crowding out effects). Second, by employing a panel data technique, the empirical specification controls for unobserved time and area characteristics. Third, the analysis explores further identification concerns. For example, cyclical and macroeconomic trends may still affect the absorption of technological shocks (Acemoglu and Autor 2010). In fact, while general business cycles can be captured by time trends, industry specific shocks challenge the causality of the relationship of interest. For instance, trade and technology could play a mutually reinforcing role in shaping local employment due to their concurrency and interdependence (Autor, Dorn, and Hanson 2013). The analysis tests explicitly for this interdependence by controlling for import competition. In addition, anticipation effects of future technological shocks in specific industries and locations may lead to different incentives to adopt new technologies (Chennels and Van Reenen, 1999). This is the case, for example, if property rights coming from patents' ownership are spatially concentrated in specific locations. Despite the fact that these anticipation effects are less likely to drive the absorption of technological advances systematically, the analysis explicitly accounts for this further aspect.

The remainder of the paper is organized as follows: section two introduces the conceptual background and the key methodological problems in the analysis of the technology-employment nexus when the spatial scale of labour market is taken into account. It discusses the estimation approach with a particular focus on the main identification challenges. Section three describes the data used for the empirical investigation, including a discussion of patent records and additional data sources. Section four presents the findings of the study along with several checks on robustness while also deepening the scope of the analysis by considering the impact of technological change across different typologies of workers and subsamples of geographical units. Finally, section five concludes the paper.

2. *Conceptual Framework and Empirical Approach*

2.1 Conceptual Framework

In the effort to conceptualize the impact of changes in technological trajectories on employment outcomes the economics literature has traditionally identified two different channels: the direct effect of technological change on employment in terms of labour saving, due to the substitution of workers and new technologies performing similar job tasks on the one hand, and its indirect effect passing through compensating mechanisms associated with increasing productivity and growth on the other. In this perspective technological changes do create and destroy a large amount of jobs, but where they are created and destroyed depends from the highly dynamic process shaped by the content of specific technological innovations, the speed of adoption and the economic activities to which the application of these new technologies is more significantly related.

Suppose that we consider changes in aggregate technological trends at international level. How would such shocks affect local labour markets in a specific country? The statistical appendix provides an explanation of the dynamics at play drawing from the econometric literature on common shocks (Andrews 2005, Bai 2009). Changes in technological trajectories are interpreted as a common shock (or an observable time trend component) affecting a certain sample population by means of a given factor of loading (the sectorial composition of local labour market areas), which is expected to be heterogeneously distributed across space[3]. Therefore local labour market areas are treated as sub-units with different levels of exposure to aggregate technological shocks as the result of regional variation in their industrial structure.

In addition to that differences in the pervasiveness of aggregate technological changes also relate to the speed of adjustment to technological shocks, which are expected to be more easily absorbed in areas characterised by a richer knowledge base and a wider portfolio of economic activities. Places with greater technological capabilities are more able to adapt to changes in technological trajectories and to exploit the opportunities of these new scenarios. Similarly areas

[3] See Appendix A for further explanations.

benefitting from urbanization economies, in terms of diversification of the available portfolio of economic activities, may absorb more quickly these aggregate shocks thanks to compensating mechanisms operating at the local level through phenomenon of industrial branching.

Spatial heterogeneity in terms of both the degree of exposure and the capability to absorb and react to changes in technological trajectories explain why aggregate studies fail to provide a comprehensive understanding of the link between employment and technological change.

2.2 Estimation Strategy

The impact of aggregate technological changes on local labour market outcomes is investigated by looking at employment figures across Travel to Work Areas (TTWAs) defined as functional units and constructed in order to be self-containing local labour market areas. Statistics at TTWA level are provided on people living and working in each geographical area, limiting the potential bias coming from commuting flows and representing a reasonable proxy for local job search area. More specifically, TTWAs are groups of wards, including both urban and non-urban areas, for which at least 75% of the resident economically active population works in the area, and for which at least 75% of individuals working in the area live in the area.

The estimation is performed employing two way panel data techniques to control for area and time unobserved characteristics. The equation takes the following form:

$$Employment_t^c = \alpha_c + \mu_t + \beta_1 Technological\ Change_t^c + \beta X_t^c + \varepsilon_t^c \qquad (1)$$

Where $Employment_t^c$ is the dependent variable measuring the employment rate in TTWA c at time t, $Technological\ Change_t^c$ is the variable of interest accounting for the role of technological change in local labour market areas. A vector of additional area level controls (X_t^c), has been also added, α_c and μ_t are area and time fixed effects respectively and ε_t^c is the error term.

It is worth noting that the dependent variable in equation (1) refers to total employment (in both services and manufacturing). Despite patents being more representative for innovation in the manufacturing industry, this choice makes it possible to account for compensating mechanisms operating in each labour market across typologies of workers, job tasks and sectors. As acknowledged by Autor and Dorn (2013), local labour markets may differentially adapt to changes in technological trajectories and the increased employment in the service sector is often the result of such adaptation mechanisms. Hence, a focus on employment outcomes in manufacturing may only provide a partial view of such adjustments.

The measure local-labor-market exposure to technological change is based on the regional variation in their industrial structure. More explicitly, the existing stock of patents granted by the USPTO at time *t-1* for each sector *s*[4] is multiplied by the share of firms per sector in each TTWA *c* in 1998. The composite indicator is obtained by summing the patent activity for all sectors by TTWA *c* and time *t*.

$$Technological\ Change_{c,t} = \sum_s (Firms_{c,1998}^s \times Patents\_Stock_{t-1}^s) \qquad (2)$$

The above measure of technological change is based on sound exogeneity conditions.

First, the stock of patents granted is based on data from the USPTO. As previously acknowledged, patents granted by the USPTO can be reasonably considered a better proxy for international technological trends that are exogenous with respect to British local labour market

[4] Defined at 2 digits NACE (Rev 1) level.

dynamics. Second, some key features of the shift share structure associated to Bartik (1993) and popularized by a number of recent contributions (Card 2007, Moretti 2010 among others) are exploited. The initial share of firms per sector in 1998 in each TTWA is used to attribute the impact of technological change to each local labour market. This further implies an assumption that, in the absence of specific shocks, each TTWA would have been affected by shifts in technological trajectories by means of its pre-existent sectorial structure. The adoption of a shift share structure allows the effect of technological change to be disaggregated while factoring out the concurrent role played by the evolution over time in the local industrial structure. At the same time, it limits any concerns associated with the possibility that the impact is driven by crowding out effects on British firms due to increasing competition in sectors experiencing greater technological progress overseas.

2.3 Further Discussion on the Identification Approach

Additional considerations should be given to the conditions under which the identification approach used in this study may fail. First, cyclical and macroeconomic trends may affect the absorption of technological shocks (Acemoglu and Autor 2010). While general business cycles are likely to be captured by time trends, industry specific shocks may still be driven by omitted variables correlating with my measure of technological change. The most relevant concern in this context regards the role of international trade. Trade with low-wage countries may in fact depress wages and employment in the industries (Artuc, Chaudhuri, and McLaren 2010), occupations (Ebenstein et al. 2013) and regions (Autor, Dorn, and Hanson 2013) that are more exposed to import competition. More relevantly, the existing literature has yet to reach consensus on the degree to which trade and technology should be seen as distinct phenomena or, rather, two sides of the same coin. An obvious association between the two arises from their concurrence (Autor, Dorn and Hanson, 2013). Many industrialized countries have been exposed to both rapid technological change (e.g. computerization, rise of the green economy) and growing international trade (e.g., the rise of China). Secondly, observational evidence seems to support their interdependence. As falling trade and transport costs stimulate the offshoring of production, in particular in low tech industries and for “routinary” job tasks, home activities tend to become more productive (Grossman and Rossi-Hansberg 2008) and more technologically intensive. This suggests the possibility of observing both increasing import from emerging players and a more pervasive effect of technological change. The concurrent role of trade and technology, in particular in the absence of convincing evidence on the independence between the two phenomena, requires more investigation. For this reason, the analysis will explicitly provide evidence on this dimension to account for the potential correlation between technological change and import competition.

Second, the impact of aggregate technological shifts may be more significant in certain areas as a consequence of specific structures and characteristics of the local production system even in the absence of a genuine causality. Anticipation effects of future technological shocks in specific sectors and areas may provide incentives toward the adoption of new technologies (Chennels and Van Reenen, 1999) and in turn employment demand for specific professional profiles. In respect to this, it is reasonable to assume that, in absence of specific conditions affecting the incentive of firms to adopt new technologies, anticipation effects of future technological shocks are unlikely to impact substantially on the decision to carry out technological investments (Harrison et al. 2008). Moreover, the measure of technological change employed, which is based on a shift share methodology, should mitigate the possibility of systematic anticipation effects. However, it can still be argued that the concentration of ownership advantages linked to the legal rights coming from the patenting procedure (Van Reenen and Bloom, 2002) in specific sectors and locations may represent a possible concern. To deal with this issue, the analysis will also account for heterogeneity in the attitude towards patenting by firms located in different labour market areas.

3. Data

3.1 Patents as a measure for technological change

Patents data has been widely used as a measure for technical change in the literature (Griliches et al. 1987; Basberg 1987; Hagedoorn and Cloodt 2003). They represent a direct outcome of the inventive process, and more specifically of those inventions which are expected to have a commercial impact (Archibugi and Pianta 1996). Furthermore, because obtaining a patent is costly and time consuming, applications are likely to be filed only for inventions that are particularly valuable and for which the benefits outweigh the cost of the process. Finally, patents statistics are available by technical fields (based on the technological classes provided by the International Patent Classification - IPC) allowing both the rate and direction of technical change to be investigated. These features explain why patents have been extensively exploited in the literature and have been widely used to investigate both the impact and determinants of technical change and why they have been preferred to other measures such as investments in R&D and total factor productivity (TFP)[5].

[5] Adopting TFP as measure for technological change implies capturing the effect of technology as a residual that may indeed reflect a number of omitted variables. Trends are likely to be picking a lot more than just technical change (Chennels and Van Reenen, 1999), casting doubts on the reliability of such a measure. Direct proxies for inputs, such as R&D expenditures, are widely available and measured in terms of unit of currency but they provide a poor representation of technological change. The amount of inputs, in fact, may not automatically be associated to innovative outputs and R&D measures are traditionally affected

Exploiting the idea of patents as a stock of blueprint technologies that can generate economically viable innovations when economic conditions are favourable (Van Reenen 1997), potential shifts in technological trajectories have been measured in terms of the stock of patents granted by the US Patent Office (USPTO). In this context, past patenting activities should not be interpreted as a determinant of current employment, but instead as a potential determinant of the current probability to innovate.

Patents granted rather than patent applications have been used to limit the problems associated to the unobserved quality of inventions while stock rather than flow measures have been applied since the benefits from patents are expected to be persistent over time (Bloom and Van Reenen, 2002). More relevantly, US patents have been preferred to British records for several reasons. First, the US Patent Office (USPTO) has a longer history and it more reasonably reflects the actual stage of the technological frontier, providing a better proxy for international technological trends. Second, patents granted by the USPTO, rather than the UK or European Patent Office (EPO), are expected to provide a more exogenous measure with respect to British economic and innovative trends.

Data on patents granted by the USPTO is available from the 1960s, however, yearly count data with detail on the industrial sector (converted at NACE-Rev1 based on the IPC classification from Eurostat) are only available from 1977 onwards. Information on the sectorial classification

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by a "selectivity" problem arising from the fact that not all firms are willing to report such information. Alternative input measures, such as, for example, innovative investments in machinery and equipment, also encompassing computerization trends, are difficult to adapt to any time series context since the passage of time changes the significance of using a particular type of technology (Chennels and Van Reenen 1999) and tend to suffer from significant simultaneity biases (i.e. firms may shift towards different technologies in response to changes in the nature and typology of available workers). More importantly, they are likely to provide a narrow definition of technological change targeted to the emergence of specific trends.

is considered as key in accounting for the transmission mechanism of major technological shocks (Vivarelli 2011). This explains why, despite the shorter time series, only data starting from 1977 is exploited. The number of patents granted by the USPTO is shown by year in Figure 1.

The lower degree of patenting activity at the end of the time series reflects a truncation due to the expected lag (generally 18 months) between patent application and publication and data dissemination. While the former aspect is unlikely to affect the reliability of my measure of technological change, the fact that data is only available from 1977 onwards may raise some concerns. The lack of data pre-1977 may, in fact, disproportionately affect stock measures for early years. Hence, alternative methodologies to construct the stock of patents granted have been used as a robustness check. In addition to the preferred measure, calculated adopting a depreciation rate of 30% (as in Cockburn and Griliches 1988 and Bloom and Van Reenen, 2002), stock measures are also constructed adopting a 15% depreciation rate (as in in Hall et al, 1999), a 5 years lag (as in early studies such as Van Reenen 1997, Machin and Van Reenen 1998, Smolny 1998, Blanchflower and Burgess 1999) and the raw number of patents over the whole period. Consistent results across these different measures should provide convincing evidence on the reliability of the preferred proxy.

The total number of patents by decade and sector (Nace-Rev1) is reported in Table 1. As expected, patents data are mainly representative for innovation in manufacturing. Table 1 also shows that the data understates innovation in services. However, this is not necessarily a key issue in the context of this paper, which focuses on the impact of technological change - measured by patents stocks - on employment outcomes. Jobs in the service sector are, in fact, more likely to be an effect rather than the cause of better economic performance (Moretti, 2012), and a measure of technological change based on manufacturing may still provide a reliable proxy for the impact of shifts in technological trajectories on the economic prospects of local economies. The number of patents has increased over time and it is characterized by a distinctive sectorial composition (Figure 2) with traditional high-tech sectors, such as Manufacture of electrical and optical equipment (DL) and Manufacture of chemicals and chemical products (DG), explaining more than the 60% of the total number of patents over the period 1977-2006.

However, from a dynamic perspective, it is worth noting that the increase in the total number of patents starting in the early 90's has also been accompanied by specific sectorial trends. The most remarkable is the relevant raise in the patenting activity for Manufacture of coke, refined petroleum products and nuclear fuel (DF), Manufacture of electrical and optical equipment (DL) and Manufacture of transport equipment (DM) and the moderate decrease for Manufacture of pulp, paper and paper products (DE), Manufacture of chemicals and chemical products (DG) and Manufacture of rubber and plastic products (DH). Such changes reasonably reflect macroeconomic technological trends varying across sectors and time.

The relevance of the sectorial dimension in analysing the evolution of technology over time supports the need of further attention to this aspect. The degree of exposure and related impact of technological change on local labour market areas is substantially mediated by their industrial composition. This implies that the sectorial dimension may represent the missing link in explaining heterogeneity in territorial responses to aggregate changes in technological trajectories.

3.2 Additional data

The investigation relies on a novel dataset providing a balanced sample for the period 2000-2007. A description of all the variables used and descriptive statistics are reported in Table 3.

In addition to patents data provided by Eurostat, which were adopted to construct the measure of technological change, a number of additional sources have been exploited.

The structure of the local production system and, in particular, the share of firms in manufacturing by 2 digits Nace-Rev1 at 1998 – which was used as baseline to construct the regressor of interest - comes from the Business Structure Database (BSD), derived from the Inter-Governmental Department Business Register (IDBR). The BSD covers the period 1997 to 2011 and provides data on employment, sector of activity, birth and death date for 7 digits postcodes. For 2004, the ONS estimated that the businesses listed on the IDBR accounted for almost 99 per cent of economic activity in the UK. This suggests the possibility to geo-localize each firm while maintaining a representative sample.

Data on employment outcomes and additional local area controls come from the Labour Force Survey (LFS). The UK Labour Force Survey (LFS) is a quarterly representative survey of households living at private addresses in the United Kingdom conducted by the Office for National Statistics (ONS). The ONS started collecting this information in 1973 as a biannual survey, which was later changed to an annual survey and, finally, to the current quarterly structure in 1992. The analysis in this study is restricted to the period 2000 - 2007 for which consistent quarterly information is available. Quarterly data, sampling around 60,000 households, was pooled to construct yearly figures. The LFS also provides data on employment and demographic characteristics and, as a result, it is also possible to extract detailed information on employment by skills and occupational categories. Skills are measured by educational achievements with high skilled individuals defined as people holding a degree or HE qualification (NVQ4), intermediate skilled individuals as holding an A-level or at least 5 GCSE's A-C grade qualification (NVQ3) while low skilled individuals are defined as those having other or no qualifications (NVQ1). Occupational categories are defined on the basis of the standard occupational classification (SOC03) with high skilled occupations encompassing senior/associate pro and tech-intensive occupations, intermediate skilled occupations encompassing admin and sec/skilled occupations and low skilled occupations encompassing PPS/sales/routine/other occupations.

Data for patent ownership come from the KEINS database (Lissoni, Sanditov, and Tarasconi 2006), this is a cleaned version of the EPO dataset to solve problems associated to misspelling and misreporting of inventors' and assignees' names. The number of patents granted to firms located in each local labour market area in the last three years is taken as a measure of attitude toward patenting by local economic actors[6].

Data on international trade come from the UN-COMTRADE database. World Bank COMTRADE data provides information on trade flows by year and sectors and is used to construct an indicator for import competition to control for alternative sources of change in employment.

[6] See Appendix B for further information.

4. *Evidence of the impact of technological change on employment outcomes in British local labour markets*

4.1 Main results

Results for the main specification of the model are reported in Table 4. The estimation is based on panel techniques to control for time and area fixed effects.

Column 1 accounts for the role of technological change while controlling for the skills structure of the workforce, proxied by the share of highly and intermediate skilled individuals. The regressor of interest is significant at the 1% level and negatively associated to employment suggesting that changes in technological trajectories have a negative effect on local employment. Interestingly, controls for the skill structure of the population are strongly significant and positively associated to employment outcomes, confirming the role of education as a strong predictor for finding employment. The negative relation between technological change and local employment also remains statistically significant when additional regressors are included in the analysis. Column 2 controls for wage level, which has been shown to be a relevant dimension in the existing literature. Compensating mechanisms within the labour market may, in fact, pass through decreasing wages rather than through overall employment levels – i.e. the labour-saving effect of new technologies is compensated for by price adjustments (Neary 1981, Sinclair 1981, Jackman and Layard 1991). Column 3 includes additional controls for the demographic structure of the population, proxied by share of young people, which is negatively and significantly correlated to employment, and females.

Robustness checks on the main specification are reported in Table 5. Different proxies (as discussed in section 3) are alternatively employed to check whether the results are sensitive to measurement issues. For example, Column 1 (Table 5) uses a depreciation rate of 15% rather than 30% as a slower depreciation rate may provide suggestive evidence on the relevance of the truncation in patents data in 1977. Column 2 includes a 5 year lag applying the “rule of thumb” customary in early studies while column 3 employs the total count of patents since 1977. The impact of technological change remains consistent in terms of sign with some not very remarkable variations in the magnitude of the coefficient.

Finally column 4 includes a proxy for patents ownership. Patents may, in fact, provide exclusive rights on new technologies generating valuable real options for the owners (Bloom and Van Reenen 2002). This implies that differences in the spatial distribution of patents’ ownership may shift firms’ incentive to adopt new technologies. Results do not vary with respect to the baseline specification[7].

The analysis is complemented by estimates of the qualitative impact of technological change on employment. The main specification is replicated substituting the dependent variable with employment rate for high, intermediate and low skilled individuals. The results are reported in Table 6.

Column 1 shows the regression for the high skilled employment rate while estimates for intermediate and low skilled are presented in column 2 and 3 respectively. Technological change, despite maintaining its negative sign in all specifications, is statistically only significant in the case of intermediate skilled workers who seem to be paying the greatest cost for changes in technological trajectories. Results also remain robust when occupational categories are used. Individuals employed in intermediate skilled occupations are significantly and negatively

[7] See Appendix B for further information.

affected by technological change (Column 5) while no substantial impact is found for high and low skilled occupations (Column 4 and 6 respectively). This evidence correlates with a number of recent studies documenting the progressive complementarity between high and low skilled workers and the increasing polarization of the workforce. It also contributes to the generalization of these results due to the adoption of a wider measure of technological change.

4.2 Alternative explanations

The role of international trade as an alternative explanation for variations in employment outcomes has found support in the existing literature (Autor, Dorn and Hanson, 2013). Technological change and increasing import competition may be concurrent aspects associated with the progressive offshoring of production. The expected positive correlation between the two phenomena suggests there is a risk of an underestimation of the negative impact of technological change on employment outcomes. In addition, foreign firms may increase competition in specific segments damaging the position of workers employed in mature industries (Machin and Van Reenen, 1998). This implies that the impact of international trade may also be heterogeneous across the skill distribution. To test for this possible concern, the analysis adopts the share of import from China and India for each 2 digit sector in the last 3 years[8] to proxy the level of import competition. This impact is then estimated for each local labour market by employing a similar shift-share structure as the one adopted to construct the measure of technological change.

[8] Note that a 5 year lag has also been used with little evidence of substantial change. Import flows from China and India were chosen due to their emerging role as leading global export countries in particular with respect to manufacturing (evidence on this for the Chinese case has recently been provided by Autor, Dorn, and Hanson (2013) and to their traditional trade relations with the UK (in the Indian case). The hypothesis has also been tested varying the sample of countries and constructing the measure of import competition based on non-OECD countries as in Machin and Van Reenen (1998).

It allows the impact of import competition to be accounted for while factoring out the potential concurrent role of changes in the industrial composition of local labour markets[9].

As expected the regressor is negatively correlated to employment. Controlling for import competition also increases, albeit negligibly, the magnitude of the coefficient of interest, supporting the expectation concerning a possible attenuation bias in baseline results. The variable is, however, only marginally significant and the measure of technological change is not substantially affected by the inclusion of this additional control (Table 7, Column 1).

These results are also in line with previous findings when employment by skills is taken as the dependent variable. While foreign competition seems to have a negative effect on employment, this impact is not particularly strong and it does not affect the magnitude and significance level of the coefficients of interest.

4.3 Heterogeneity across space

The results suggest that changes in technological trajectories affect negatively employment outcomes in British local labour market areas. This evidence is not surprising in light of the persistent uneven pattern of employment change in Britain during the last few decades. Hot spots of unemployment and social deprivation demonstrate that labour market adjustments have been far from perfect. Turok and Edge (1999), analysing labour market dynamics in Britain between the beginning of the ‘80s and the mid ‘90s, show that changes in employment have outpaced shifts in population, further suggesting that internal migration flows do not respond efficiently to employment shocks. National shocks, such as de-industrialization trends, have been responsible

[9] See Appendix B for further information.

for major job losses in areas such as Northern England and the Midlands. Nevertheless, the intensity of compensation mechanisms has been much lower than expected and employment gaps within Britain have continuously increased over the last two decades. This evidence is supported by the negligible role played by out migration as a potential adjustment mechanism.

The nature and intensity of labour market dynamics in the 80s' and 90s' supports the idea that labour markets in Britain are intrinsically local in their functioning and that major common shocks are rarely fully outpaced by nation-wide adjustments. Changes in technological trajectories are more likely to impact disproportionately on areas characterized by weaker labour markets, weaker or overspecialized industrial structures and insufficient technological capabilities.

This evidence is generally confirmed in the data by a number of empirical checks. The impact of technological change on employment was investigated by splitting the sample between urban and non-urban areas. Urban areas are assumed to be characterized by a thicker labour market and to benefit from urbanization economies arising from the coexistence of different industries clustering in specific spatial contexts. These structural characteristics may help to absorb employment changes due to shifts in technological trajectories more efficiently since workers experiencing job losses due to negative productivity shocks have a higher probability of finding an alternative. Table 8 reports results for both subsamples[10].

Column 1 shows the estimation for the sample of urban TTWAs while Column 5 refers to non-urban areas. Despite the persistence of a negative sign, there is no evidence of a significant effect

[10] The distinction between urban and non-urban TTWA is provided by the Office of National Statistics and is available in the ONS Postcode Directory (ONSPD).

of technological change in urban areas while its impact remains negatively and significantly correlated to employment in non-urban areas. This finding confirms the ex-ante belief that areas characterized by a more dynamic labour market are reasonably more able to absorb structural changes. Results are also reported by skills groups. Interestingly, despite the difference in the magnitude of the coefficient, which is more pronounced in the case of non-urban areas, the negative impact on intermediate skilled individuals remains robust across samples. This correlates with the existing evidence on job polarization in British cities characterised by a progressive reduction of middle skilled jobs and a significant increase in the share of manual jobs (Goos and Manning, 2008). It is, however, also worth noting that the sample of urban areas in Britain is characterized by a relevant heterogeneity with a consistent subsample of cities, affected by longstanding patterns of industrial decline, which may partially drive this result.

To further exploit this dimension while comparing areas with more homogeneous technological capabilities, the full sample of British TTWAs was split according to their degree of specialisation in medium high and high tech industries[11]. High tech industries are characterized by higher level of R&D investments and innovative efforts (OECD, 2011). Areas with a greater specialization in high value added industries are expected to have richer knowledge bases and greater capabilities to cope with the challenges resulting from changes in technological trajectories. Following the classification provided by the OECD, the sample of British TTWAs was split according to their average share of firms in medium high and high tech sectors over the

[11] High-tech industries encompass high and medium - high technology industries (chemicals; office accounting and computer machinery; radio, TV and telecommunication instruments; medical, precision and optical instruments; electrical machinery and apparatus, n.e.c.; machinery and equipment; railroad and transport equipment, n.e.c.).

period 2000-2007[12]. On average, almost 2.4% of firms in British Local labour market areas are specialised in medium-high and high tech industries with a cross sectional variation ranging from 1.8 to 3%. Estimates for the two samples are reported in table 9.

Column 1 refers to areas with a share of high tech industries below the median, while Column 5 performs the estimation for those areas with a share of high tech industries above the median value. As expected, the negative and significant impact of technological change remains strongly concentrated in the lower tier of the distribution. Areas with a poor specialization in high value added activities are more likely to experience the negative effect of changes in technological trajectories since they are less able to engage with new technological trends and experience virtuous cycles of productivity and growth. Interestingly, the evidence in favour of a progressive workforce polarization remains persistent in areas characterized by specialization in mature industries (Table 9, Column 3), but is much weaker and only marginally significant for places with a high share of high tech activities (Column 7). Areas with traditional specializations and lower technological capabilities are those facing the highest risks. In these contexts, people employed in "routinary" activities tend be more affected by the negative consequences of changes in technological paradigms.

[12] The average share of high tech industries in respect to its variation over time was preferred due to the stability in sectoral specialization of British TTWAs over the period under analysis.

5. *Conclusions*

The link between technological changes and employment has been widely investigated in the economics literature and its magnitude and sign has generated broad social and political concerns.

Spatial heterogeneity, in terms of degree of exposure and capability to exploit the opportunities coming from changes in technological trajectories, has been recently identified as a key dimension for investigation as it may generate heterogeneous responses to aggregate technological shocks, accentuating the gap between different geographical areas.

This paper contributes to the existing literature by incorporating the recent attention towards the role of the spatial scale of labour market adjustments, while developing a comprehensive investigation based on a more generalizable a widely used proxy of technology and a wider range of labour market outcomes.

Exploiting a novel database complementing different sources of micro data and utilizing a widely adopted measure of technological change, the paper shows that, when the spatial dimension of the labour market is taken into account, technological change is negatively associated to employment. This evidence correlates with previous findings showing that regional employment gaps in Britain tend to persist over time and that nationwide compensating mechanisms have been unable to counterbalance the negative trends of deindustrialization. Results are robust to measurement and endogeneity concerns, to the inclusion of additional regressors and testing for alternative explanations. The relevance of the spatial dimension of the labour market and the need for further investigation of this issue is also confirmed by the empirical evidence concerning the particularly strong negative impact of technological change in areas characterized by weaker agglomeration economies and lower technological capabilities. Different places are heterogeneously exposed to changes in technological scenarios and have different capabilities to respond to the challenges that creative destruction ultimately creates. In addition, the paper also provides evidence for the progressive polarization of the workforce in Britain. The negative impact of technological change remains mainly concentrated in the intermediate tier of the skill distribution also when more general measures of technological change are taken into account.

Places characterized by slacker labour markets, weaker agglomeration economies, mature specializations and weaker technological capabilities are more affected by shifts in technological trajectories. In these contexts, individuals with lower levels of distinctive skills employed in "routinary" activities and mature industries pay the greatest cost, and face extraordinary challenges in re-placing themselves into the job market. Policy makers should, therefore, take into account more seriously the implications concerning the spatial dimension of the labour markets. Differences in the industrial structure of local labour market areas and endogenous technological capabilities may generate heterogeneous responses. Spatial heterogeneity remains a key dimension to consider since it may substantially challenge the functioning and effectiveness of nationwide policies.

A - Statistical Appendix

Considering the following model;

$$Y_{c,t} = \beta_0 + \beta_1 X_{ct} + U_{ct} \quad (3)$$

Where Y_{ct} is the dependent variable, X_{ct} is an observed regressor and U_{ct} is an unobserved error component.

In this context a simple model allowing for common shocks in equation 3 implies that $U_{ct=}C_t + \varepsilon_{ct}$ where C_t is a random shock that is assumed to be common to all observations *i* at time *t*.

It is possible to assume that common shocks across observations arising in the form of a vector of random variables C_t affect all population units *i* through an additional observable dimension S_{ct} such that conditional on C_t, $\{S_{c,t}: i = 1,2 \ldots\}$are i.i.d.

This assumption is compatible with any common shock that is assumed to have a heterogeneous effect across population units (Andrews, 2003).

In this context, the complementary variable S_{it} represents the factor loading the effect of the common shock across different population units. This implies an assumption that the dependent variable Y_{ct} depends on a common shock $\{C_t$: t=1,2…} through the vector $S_{c,t} = (C_1 S_{c,1}, C_2 S_{c,2} \ldots C_t S_{ct})$.

In this analysis, the common shock is assumed to differ across population units in a continuous manner, meaning that the factor loading its impact, S_{ct}, is measured as a continuous component and that its effect varies continuously across *i* depending on S_{it}.

Technological change, interpreted as common shock and measured by means of patents granted is attributed to each population unit by means of the share of firms in each TTWA. The attribution criterion follows not only a spatial but also a sectorial criterion. This implies that both the measure of aggregate common shock C_t and the vector $S_{c,t}$ exploit the sectoral dimension to account for the impact of the common shock on each population unit.

This extension, in respect to the literature on common shocks and additive terms, is justified in the light of existing findings on the link between technological change and employment where the sectorial dimension is traditionally considered as a key channel mediating the probability of absorbing major technological shocks.

B - Variables Appendix

Patent Ownership

The patent ownership variable is constructed according to the number of patents granted to firms located in each TTWA, based on the following structure:

$$Patent\ Ownership_{c,t} = N\ of\ patents\ granted_{t-3} \qquad (4)$$

Location for patenting firms (reported as assignee in the patent document) are identified for 7-digits postcodes and then allocated to each TTWA *c*, based on the National Postcode Directory provided by the ONS to merge different UK areas. Patents ownership is calculated according to the number of patents granted to local firms in the previous 3 years. Note that robustness checks for patents granted to local firms in the same year, in the last five and ten years, were performed without evidence of any significant changes.

Import Competition

The variable aimed at proxying import competition in local labour market areas is constructed following a similar strategy as that adopted for the key measure of technological change. This implies that the impact of recent import flows from China and India are attributed to each TTWA by means of their pre-existent economic structure. This strategy follows the insights from a recent contribution by Autor et al (2013) modelling the local labour market impact of import competition from China for the US. They argue that the sectorial dimension of each spatial unit is the factor loading the intensity and magnitude of the effect at the local level.

In more detail, the variable used in this study takes the following form:

$$Import\ Competition_{c,t} = \sum_s (Firms^s_{c,1998} \times Import\ flows^s_{T,t-3}) \qquad (5)$$

Import flows from China and India in the last 3 year by sector *s*[13] is multiplied by the share of firms per sector in each TTWA *c* in 1998. The composite indicator is obtained by summing activity in all sectors by TTWA *c* and time *t*. It is worth noting that the structure above, as for the main regressor of interest used here, allows for the impact of recent import competition to be accounted for while factoring out the contextual role of changing industrial structure in local labour markets.

[13] Defined at 2 digits NACE (Rev 1) level.

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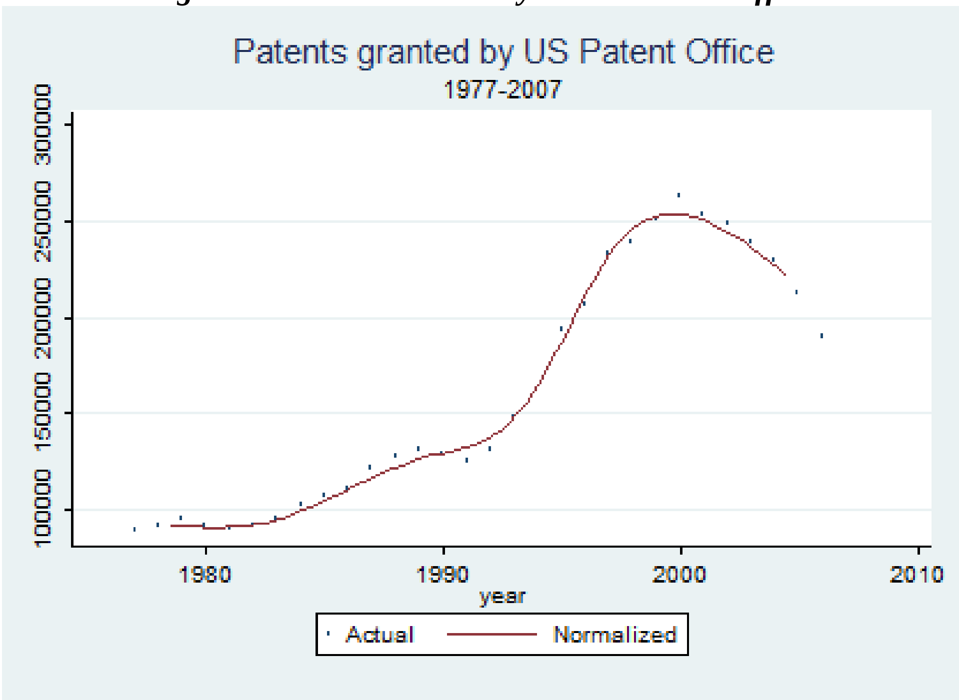
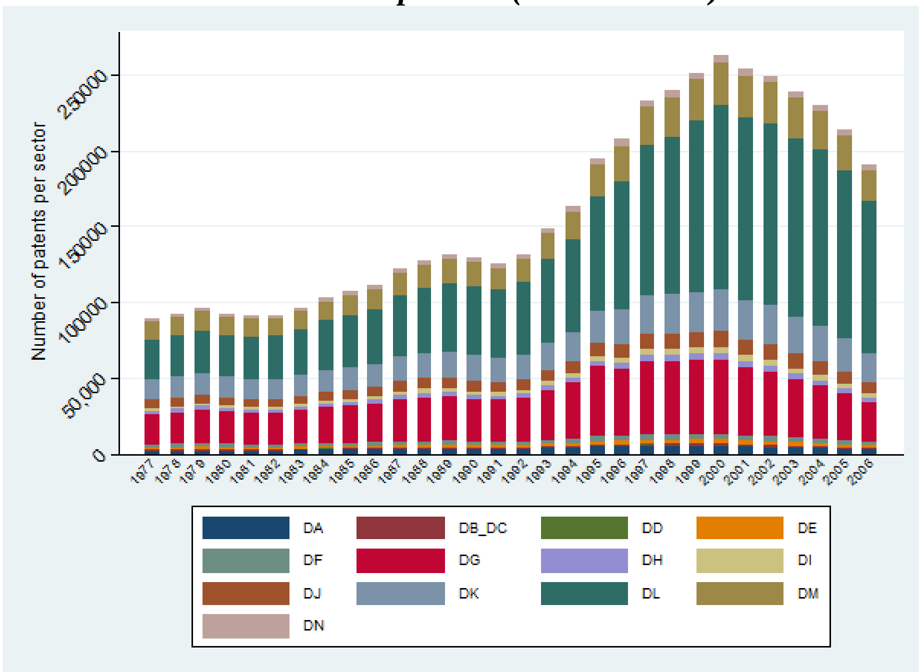
Tables and Figures

Figure 1: Patents Granted by the US Patent Office



Source: Innovation Database - EUROSTAT

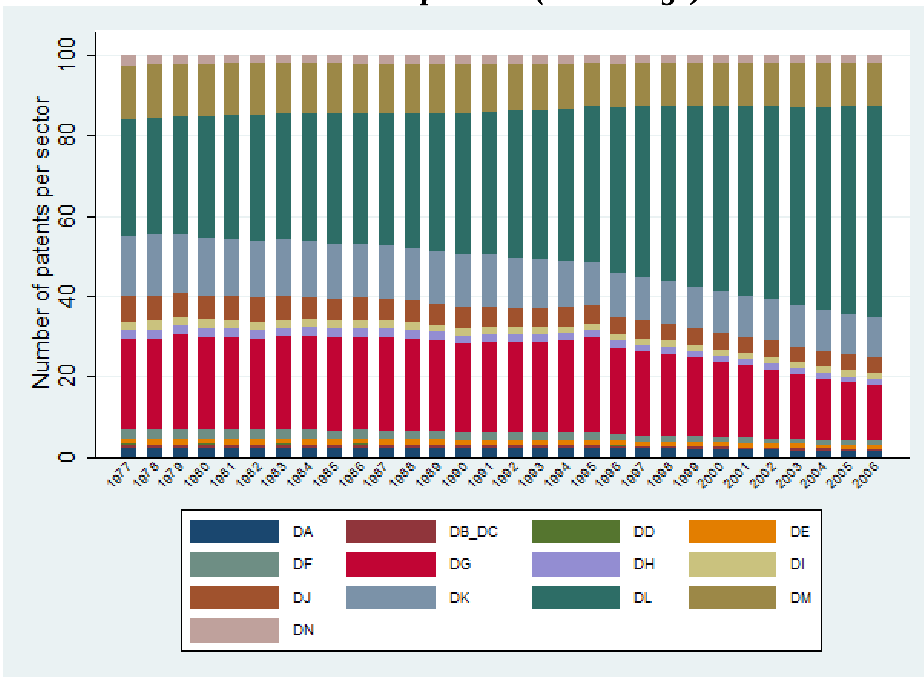
Figure 2: Patents Granted by the US Patent Office
Sectorial Composition (Patents Count)



Source: Innovation Database – EUROSTAT

Note: DA "Manufacture of food products, beverages and tobacco", DB-DC "Manufacture of textiles and textile products" and "Manufacture of leather and leather products", DD "Manufacture of wood and wood products", DE "Manufacture of pulp, paper and paper products", DF "Manufacture of coke, refined petroleum products and nuclear fuel", DG "Manufacture of chemicals and chemical products", DH "Manufacture of Rubber and Plastic Products", DI "Manufacture of other non-metallic mineral products", DJ "Manufacture of basic metals and fabricated metal products", DK "Manufacture of machinery and equipment", DL "Manufacture of electrical and optical equipment", DM "Manufacture of transport equipment", DN "Manufacturing n.e.c."

Figure 3: Patents Granted by the US Patent Office
Sectorial Composition (Percentage)



Source: Innovation Database – EUROSTAT

Note: DA "Manufacture of food products, beverages and tobacco", DB-DC "Manufacture of textiles and textile products" and "Manufacture of leather and leather products", DD "Manufacture of wood and wood products", DE "Manufacture of pulp, paper and paper products", DF "Manufacture of coke, refined petroleum products and nuclear fuel", DG "Manufacture of chemicals and chemical products", DH "Manufacture of Rubber and Plastic Products", DI "Manufacture of other non-metallic mineral products", DJ "Manufacture of basic metals and fabricated metal products", DK "Manufacture of machinery and equipment", DL "Manufacture of electrical and optical equipment", DM "Manufacture of transport equipment", DN "Manufacturing n.e.c."

Table 1: Patents Granted by the US Patent Office by Sector and Decade

	Total Patents	Share	Freq.
Decade			
1977-1986	385619.00	0.20	0.20
1987-1996	579892.40	0.30	0.50
1997-2006	974762.20	0.50	1.00
Industry			
DA	39916.37	0.02	0.02
DB-DC	13098.37	0.01	0.03
DD	1787.80	0.00	0.03
DE	23580.91	0.01	0.04
DF	32225.79	0.02	0.06
DG	387761.60	0.20	0.26
DH	36371.69	0.02	0.28
DI	32235.21	0.02	0.29
DJ	90079.57	0.05	0.34
DK	222423.80	0.11	0.45
DL	803354.90	0.41	0.87
DM	203330.50	0.10	0.97
DN	54107.15	0.03	1.00

Source: Innovation Database – EUROSTAT

Note: DA “Manufacture of food products, beverages and tobacco”, DB-DC “Manufacture of textiles and textile products” and “Manufacture of leather and leather products”, DD “Manufacture of wood and wood products”, DE “Manufacture of pulp, paper and paper products”, DF “Manufacture of coke, refined petroleum products and nuclear fuel”, DG “Manufacture of chemicals and chemical products”, DH “Manufacture of Rubber and Plastic Products”, DI “Manufacture of other non-metallic mineral products”, DJ “Manufacture of basic metals and fabricated metal products”, DK “Manufacture of machinery and equipment”, DL “Manufacture of electrical and optical equipment”, DM “Manufacture of transport equipment”, DN “Manufacturing n.e.c.”

Table 2: Patents Granted by the US Patent Office – Variation across decades

	1977-1986	*1987-1996*	*1997-2006*	*Variation 77-86/87-96*	*Variation 87-96/96-06*
DA	9045.05	12953.30	17918.02	0.43	0.38
DB-DC	2963.49	4225.06	5909.82	0.43	0.40
DD	426.04	575.05	786.71	0.35	0.37
DE	5047.07	7796.44	10737.40	0.54	0.38
DF	9742.65	10344.75	12138.39	0.06	0.17
DG	85572.21	127198.30	174991.00	0.49	0.38
DH	9226.33	12228.34	14917.03	0.33	0.22
DI	7559.27	10112.58	14563.36	0.34	0.44
DJ	22878.67	29102.14	38098.76	0.27	0.31
DK	55496.96	70499.42	96427.45	0.27	0.37
DL	120045.50	213201.90	470107.50	0.78	1.20
DM	46443.68	63428.65	93458.16	0.37	0.47
DN	11172.18	18226.40	24708.57	0.63	0.36

Source: Innovation Database – EUROSTAT

Note: DA "Manufacture of food products, beverages and tobacco", DB-DC "Manufacture of textiles and textile products" and "Manufacture of leather and leather products", DD "Manufacture of wood and wood products", DE "Manufacture of pulp, paper and paper products", DF "Manufacture of coke, refined petroleum products and nuclear fuel", DG "Manufacture of chemicals and chemical products", DH "Manufacture of Rubber and Plastic Products", DI "Manufacture of other non-metallic mineral products", DJ "Manufacture of basic metals and fabricated metal products", DK "Manufacture of machinery and equipment", DL "Manufacture of electrical and optical equipment", DM "Manufacture of transport equipment", DN "Manufacturing n.e.c."

Table 3: Variable List and Sample Statistics

Variable	Description	Source	Obs.	Mean	Sd.
Employment	Employment rate - Total employment over working age population	LFS	1832	0.759531	0.050146
Employment HS	Employment rate – High Skills population (with NVQ4 - degrees / HE qualification)	LFS	1832	0.860567	0.047673
Employment IS	Employment rate – Intermediate Skills Population (with A-level or at least 5 GCSE's A-C grade qualification - NVQ3)	LFS	1832	0.778651	0.050285
Employment LS	Employment rate – Low Skills Population (with other or no qualifications - NVQ1)	LFS	1832	0.639767	0.086228
Employment HSO	Employment rate – High skilled occupations (senior/associate pro and tech-intensive occ.)	LFS	1832	0.377028	0.063035
Employment ISO	Employment rate – Intermediate skilled occupations (admin and sec/skilled trades occ.)	LFS	1832	0.373075	0.055182
Employment LSO	Employment rate – Low skilled occupations (PPS/sales/routine/other occ.)	LFS	1832	0.416173	0.04584
Technological Change (Dep.rate 30%)	Stock of patents granted (depreciated at 30%)	EUROSTAT Innovation Database	1832	64061.82	17878.59
Technological Change (Dep.rate 15%)	Stock of patents granted (depreciated at 15%)	EUROSTAT Innovation Database	1832	101322.2	27980.85
Technological Change (Lag 5)	Lagged Stock of Patents granted (5 years)	EUROSTAT Innovation Database	1832	89373.97	25078.11
Technological Change (Total Count)	Sheer stock of Patents granted	EUROSTAT Innovation Database	1832	291937.5	83178.4
Young Population	Share of population aged 24 or less over total population	LFS	1832	0.234888	0.034948
Female Population	Share of female population over total population	LFS	1832	0.494852	0.017927
High Skills Population	Share of Population with NVQ4 (degrees / HE qualification) over total population	LFS	1832	0.245666	0.057597
Intermediate Skills Population	Share of population with A-level or at least 5 GCSE's A-C grade qualification (NVQ3) over total population	LFS	1832	0.482594	0.039747
Wage	Hourly wage	LFS	1832	9.516848	1.572451
Patent Ownership	Number of patents granted to firms in each TTWA in the last 3 years	KEINS-EPO	1832	0.084731	0.020342
Import Competition	Import intensity from China and India	UN-COMTRADE	1832	0.541329	0.066976

Source: ONS/LFS-BSD; KEINS-EPO, EUROSTAT-Innovation Database, KEINS-EPO Database Bocconi University, UN Comtrade Database, Mid-Population Estimates ONS.

Note: "Employment Rate", "Employment HS", "Employment IS" and "Employment LS" refer to total working age population in each TTWA while regressors for young, high and intermediate skills and non-British population refer to the whole sample. "Employment HSO", "Employment ISO" and "Employment LSO" are constructed with respect to total employment. "Technological Change" variables are all interacted by the share of firms in each TTWA by 2 digits sector at 1998. Import competition is based on data on import from China and India by 2 digits sector over the total sum of import and export. Data on outmigration are available for years 2001-2006 and England and Wales. All regressors are taken in log except "Patent Ownership", "Technological Change" and "Import Competition" and "Non-British Population". Minimum and maximum values not reported in compliance with ONS disclosure regulations on sensible data.

Table 4: Main Results - Employment and Technological Change

Fixed Effects Estimation

Dependent Variable: Employment Rate

	(1)	(2)	(3)
Tech Change (Dep.rate 30%)	-0.0433***	-0.0436***	-0.0431***
	(0.0152)	(0.0150)	(0.0147)
High Skills Population	0.0821***	0.0829***	0.0822***
	(0.0187)	(0.0203)	(0.0205)
Intermediate Skills Population	0.1211***	0.1212***	0.1310***
	(0.0251)	(0.0252)	(0.0258)
Hourly Wage		-0.0040	-0.0078
		(0.0198)	(0.0207)
Female Population			-0.0497
			(0.0307)
Young Population			-0.0343***
			(0.0089)
Constant	-0.0802*	-0.0708	-0.1412
	(0.0448)	(0.0753)	(0.0887)
Observations	1832	1832	1832
R2	0.0819	0.0819	0.0950

Robust standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Area and year fixed effects included.

Table 5: Measurement Issues and Robustness Check

Fixed Effects Estimation

Dependent Variable: Employment Rate

	(1)	(2)	(3)	(4)
Tech Change (Dep.rate 15%)	-0.0339***			
	(0.0105)			
Tech Change (Lag 5)		-0.0390***		
		(0.0136)		
Tech Change (Count)			-0.0222***	
			(0.0071)	
Tech Change (Dep.rate 30%)				-0.0430***
				(0.0147)
Patents Ownership				0.0008
				(0.0014)
High Skills Population	0.0829***	0.0821***	0.0832***	0.0822***
	(0.0206)	(0.0204)	(0.0206)	(0.0205)
Intermediate Skills Population	0.1312***	0.1311***	0.1326***	0.1308***
	(0.0258)	(0.0258)	(0.0258)	(0.0258)
Hourly Wage	-0.0079	-0.0077	-0.0070	-0.0077
	(0.0209)	(0.0207)	(0.0210)	(0.0207)
Female Population	-0.0538*	-0.0491	-0.0556*	-0.0496
	(0.0313)	(0.0307)	(0.0316)	(0.0307)
Young Population	-0.0342***	-0.0344***	-0.0344***	-0.0342***
	(0.0089)	(0.0089)	(0.0089)	(0.0089)
Constant	-0.1464	-0.1406	-0.1492*	-0.1411
	(0.0896)	(0.0887)	(0.0902)	(0.0887)
Observations	1832	1832	1832	1832
R2	0.0974	0.0946	0.0972	0.0951

Robust standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Area and year fixed effects included.

Table 6: Technological Change, Skills and Occupations

Fixed Effects Estimation

Dependent Variables: Employment Rate High Skills, Employment Rate Intermediate Skills, Employment Rate Low Skills, Employment Rate High Skilled Occupations, Employment Rate Intermediate Skilled Occupations, Employment Rate Low Skilled Occupations

Dep. Var.	(1) Employment HS	(2) Employment IS	(3) Employment LS	(4) Employment HSO	(5) Employment ISO	(6) Employment LSO
Tech Change (Dep.rate 30%)	-0.0086	-0.0666***	-0.0496	0.0531	-0.0799**	0.0192
	(0.0269)	(0.0188)	(0.0343)	(0.0365)	(0.0361)	(0.0361)
High Skills Population	0.0345	0.0300	-0.0481	0.0713*	-0.0201	-0.0525**
	(0.0250)	(0.0205)	(0.0363)	(0.0389)	(0.0329)	(0.0239)
Intermediate Skills Population	0.0165	0.0758**	-0.0181	0.0686	0.0405	-0.0762
	(0.0325)	(0.0331)	(0.0471)	(0.0523)	(0.0499)	(0.0524)
Hourly Wage	0.0967***	-0.0419*	-0.0224	0.0341	0.0093	-0.0697
	(0.0305)	(0.0228)	(0.0676)	(0.0555)	(0.0456)	(0.0430)
Female Population	-0.0520	-0.0284	-0.1273	0.1491	-0.0929	-0.0144
	(0.0497)	(0.0391)	(0.0852)	(0.0969)	(0.0823)	(0.0760)
Constant	-0.3333***	-0.1810**	-0.6300***	-0.8632***	-0.9288***	-0.9633***
	(0.0853)	(0.0908)	(0.1855)	(0.2000)	(0.1864)	(0.1511)
Observations	1832	1832	1832	1832	1832	1832
r2	0.0294	0.0497	0.0250	0.2072	0.0766	0.0764
F	2.3132	6.7820	2.9097	27.1035	8.9246	8.0587

Robust standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Area and year fixed effects included.

Table 7: Technological Change and International Trade

Fixed Effects Estimation

Dependent Variables: Employment Rate, Employment Rate High Skills, Employment Rate Intermediate Skills, Employment Rate Low Skills

	(1)	(2)	(3)	(4)
Dep.Var.	Employment	Employment HS	Employment IS	Employment LS
Tech Change (Dep.rate 30%)	-0.0446***	-0.0090	-0.0677***	-0.0521
	(0.0148)	(0.0269)	(0.0187)	(0.0342)
High Skills Population	0.0822***	0.0345	0.0300	-0.0480
	(0.0206)	(0.0250)	(0.0206)	(0.0365)
Intermediate Skills Population	0.1305***	0.0163	0.0754**	-0.0189
	(0.0258)	(0.0326)	(0.0330)	(0.0474)
Hourly Wage	-0.0069	0.0970***	-0.0413*	-0.0210
	(0.0208)	(0.0305)	(0.0228)	(0.0679)
Female Population	-0.0501	-0.0521	-0.0287	-0.1280
	(0.0309)	(0.0497)	(0.0391)	(0.0854)
Young Population	-0.0334***	-0.0016	-0.0543***	-0.0258
	(0.0089)	(0.0164)	(0.0132)	(0.0226)
Import Competition	-0.0140*	-0.0044	-0.0105	-0.0233
	(0.0077)	(0.0130)	(0.0090)	(0.0180)
Constant	-0.1579*	-0.3385***	-0.1935**	-0.6576***
	(0.0897)	(0.0883)	(0.0915)	(0.1889)
Observations	1832	1832	1832	1832
r2	0.0970	0.0295	0.0504	0.0260
F	6.3991	2.2279	6.6522	2.9982

Robust standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Area and year fixed effects included.

Table 8: Technological change across Urban and non-Urban areas

Fixed Effects Estimation

Dependent Variables: Employment Rate, Employment Rate High Skills, Employment Rate Intermediate Skills, Employment Rate Low Skills

	URBAN				NON-URBAN			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var.	Employment	Employment HS	Employment IS	Employment LS	Employment	Employment HS	Employment IS	Employment LS
Tech Change (Dep.rate 30%)	-0.0225	0.0057	-0.0461**	-0.0213	-0.0496**	-0.0089	-0.0675***	-0.0642
	(0.0188)	(0.0225)	(0.0191)	(0.0658)	(0.0197)	(0.0358)	(0.0253)	(0.0420)
High Skills Population	0.0811***	0.0014	0.0191	-0.0136	0.0820***	0.0412	0.0323	-0.0526
	(0.0168)	(0.0206)	(0.0193)	(0.0434)	(0.0256)	(0.0307)	(0.0254)	(0.0450)
Intermediate Skills Population	0.1516***	0.0224	0.0572	0.0070	0.1283***	0.0174	0.0822**	-0.0216
	(0.0232)	(0.0350)	(0.0400)	(0.0585)	(0.0335)	(0.0407)	(0.0411)	(0.0595)
Hourly Wage	-0.0290	0.0820*	-0.0476	-0.1149*	-0.0049	0.0976***	-0.0422	-0.0068
	(0.0290)	(0.0442)	(0.0400)	(0.0663)	(0.0239)	(0.0346)	(0.0259)	(0.0770)
Female Population	0.0184	0.1020*	0.0138	-0.1314	-0.0681*	-0.0814	-0.0425	-0.1364
	(0.0509)	(0.0522)	(0.0620)	(0.1457)	(0.0361)	(0.0592)	(0.0456)	(0.0990)
Young Population	-0.0441**	-0.0277	0.0046	-0.1304**	-0.0330***	0.0020	-0.0626***	-0.0137
	(0.0173)	(0.0316)	(0.0242)	(0.0540)	(0.0098)	(0.0182)	(0.0144)	(0.0236)
Constant	-0.0360	-0.2633**	-0.0548	-0.5195**	-0.1704	-0.3465***	-0.2123*	-0.6579***
	(0.0731)	(0.1068)	(0.1065)	(0.2134)	(0.1079)	(0.1023)	(0.1077)	(0.2182)
Observations	632	632	632	632	1200	1200	1200	1200
r2	0.1256	0.0499	0.0927	0.0688	0.0944	0.0323	0.0498	0.0241
F	7.0780	2.3021	5.4326	3.6037	4.7170	1.7761	4.8891	2.0028

Robust standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Area and year fixed effects included.

Table 9: Technological Change and High Tech Intensity

Fixed Effects Estimation

Dependent Variables: Employment Rate, Employment Rate High Skills, Employment Rate Intermediate Skills, Employment Rate Low Skills

	LOW TECH				HIGH TECH			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment	Employment HS	Employment IS	Employment LS	Employment	Employment HS	Employment IS	Employment LS
Tech Change (Dep.rate 30%)	-0.0475**	-0.0064	-0.0758**	-0.0520	-0.0111	0.0198	-0.0387*	-0.0092
	(0.0237)	(0.0394)	(0.0311)	(0.0528)	(0.0172)	(0.0333)	(0.0206)	(0.0446)
High Skills Population	0.1149***	0.0751**	0.0621**	-0.0499	0.0561***	-0.0104	0.0040	-0.0223
	(0.0321)	(0.0370)	(0.0305)	(0.0612)	(0.0167)	(0.0227)	(0.0228)	(0.0362)
Intermediate Skills Population	0.1958***	0.0746	0.1608***	0.0130	0.0695***	-0.0384	-0.0082	-0.0470
	(0.0420)	(0.0451)	(0.0519)	(0.0761)	(0.0218)	(0.0450)	(0.0335)	(0.0606)
Hourly Wage	0.0158	0.1079**	-0.0279	0.0428	-0.0514**	0.0692*	-0.0631**	-0.1392**
	(0.0309)	(0.0434)	(0.0331)	(0.0999)	(0.0209)	(0.0409)	(0.0301)	(0.0609)
Female Population	-0.0845**	-0.0957	-0.0498	-0.1751	-0.0178	-0.0023	-0.0198	-0.0791
	(0.0408)	(0.0679)	(0.0492)	(0.1212)	(0.0441)	(0.0733)	(0.0622)	(0.1085)
Young Population	-0.0433***	-0.0132	-0.0824***	-0.0123	-0.0231*	0.0102	-0.0178	-0.0513
	(0.0125)	(0.0209)	(0.0179)	(0.0287)	(0.0128)	(0.0251)	(0.0191)	(0.0341)
Constant	-0.1631	-0.3158***	-0.2022	-0.7831***	-0.0718	-0.3216***	-0.1419	-0.3431*
	(0.1358)	(0.1163)	(0.1361)	(0.2831)	(0.0732)	(0.1039)	(0.1006)	(0.1995)
Observations	920	920	920	920	912	912	912	912
r2	0.1632	0.0624	0.0798	0.0197	0.0466	0.0282	0.0635	0.0599
F	6.7083	2.4675	5.7927	1.2120	2.3829	2.2871	4.1500	3.7461

Robust standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Area and year fixed effects included.

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