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Abstract

This paper investigates the effect of firms' investment in R&D on employment level and composition in UK local labour markets. We distinguish the impact of R&D across areas with different initial shares of workers in routinised occupations and industry specialisation and for different sectors, levels of education, paid employment and self-employment, and age cohorts. Drawing on two instrumenting strategies, our results consistently suggest that R&D growth, on average, exerts no multiplier effect on local employment, but changes its composition. Results differ significantly by the initial level of routinisaton. Low routinised areas experience a relative reduction in low educated employment in non tradeable services and self-employment. In highly routinised areas, low education employment is created in no tradeable services; a significant share of this is in self-employment, concentrated in the 25-34 age cohort, whereas the 17-24 cohort is negatively affected. We qualify the effect of R&D on the nature of self-employment and find no evidence to distinguish if it is driven by R&D related opportunities or necessity.

Keywords: Innovation; R&D; Employment; Self-employment; Local Labour Markets; Routinisation.

JEL: O33; J24; D3

1 Introduction

The effect of technical change on the rate, growth, and composition of employment has long been debated, since Ricardo (Freeman et al.; 1982; Freeman and Soete; 1987), to the more recent routine replacing technical change theory (RRTC) (Acemoglu and Autor; 2011). The recent concerns on the potential job-loss effect of automation and robotisation[1] have brought technological unemployment back to the forefront of the debate in academic and policy circles (Sachs et al.; 2015; Summers; 2013).

There is substantial evidence that innovating firms hire more workers, with product innovation generally having a stronger impact than process innovation, particularly in large and high tech firms, independently on the measure of innovation used.[2]

Such positive relation, though, does not account for the impact of innovative firms on the local or national labour markets, for instance through competition, market stealing, or positive externalities. Moretti (2010) has shown that in the US a new job created in a tradeable sector (e.g. manufacturing), can have a multiplier effect on the local labour market of 1-2 new jobs in non-tradeable sectors (e.g. retail, construction). If the new job is in a high tech sector, such multiplier becomes as large as six (Moretti and Thulin; 2013). Innovation measured as an increase in high tech sectors employment shares thus seems to increase jobs also in the rest of the local labour market (Lee and Clarke; 2017).

Autor and Dorn (2013) have documented an increase in employment following adoption of ICT in US local labour markets, but industrial robots seem to have the opposite impact (Acemoglu and Restrepo; 2017). The adoption of process innovation, positive at firm level, may thus have less clear cut effect when we extend to the labour market.

Results from product innovation, measured with patenting activity, also seem more ambiguous when moving from the firm to the local labour market. Gagliardi (2014) documents a negative effect of patenting activity across UK local labour market on employment, even more so in areas specialised in mature industries.

There is no evidence though on the impact of firms' investment in innovative activities on the labour market. Firms' choice to spend in R&D is strategic, and not only it might represent a trade-off with respect to other investments, but also requires a change in the firms' organisation of production and labour. It might require new skills, complementary skills, and/or replace extant ones. The literature has not devised so far a theory of the effects of R&D on employment. At the firm level, R&D demands employment in occupations requiring abstract skills (e.g. engineers). At the same time, it may lead to increased productivity and new products, which may result in an increased demand, and employment, in all occupations (Bogliacino et al.; 2012). In the local labour market, an increase in skilled R&D jobs may have a multiplier effect (Moretti; 2010), attracting more skilled workers, entrepreneurs, and unskilled workers in non-tradeable services.[3]

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[1]See, among others, Acemoglu and Restrepo (2017, 2016); Arntz et al. (2017); Brynjolfsson and McAfee (2014); Frey and Osborne (2017); Graetz and Michaels (2015); Nedelkoska and Quintini (2017).

[2]See for example Harrison et al. (2014) for evidence based on the introduction of process and product innovations across several EU countries countries; Bogliacino et al. (2012) for evidence based on large firms R&D across several countries; Coad and Rao (2011) for evidence from the US using both R&D and patenting; and Calvino and Virgillito (2018) for a recent survey.

[3]The effect may depend on whether the knowledge and technology are easy to access and create opportunities for new ventures, or whether they are strongly protected by incumbent firms (Breschi et al.; 2000).

The first contribution of this paper is to empirically estimate the impact of R&D on the level of employment. We do so for UK local labour markets. We account for two conditioning factors that have been considered separately in the literature: the local industrial structure (Gagliardi; 2014), by employing a shift share instrument that weights the national increase in R&D expenditure with local shares of employment across industries; and the initial skill composition (Autor and Dorn; 2013), by distinguishing areas with high and low shares of workers employed in routine occupations.[4]

We focus on the 2001-2011 decade in which private R&D investment (Fig. 1) and TFP, on average, have declined (Fig. 2), and employment has decreased, although less than paid employment, due to a contemporaneous steady growth of self-employment (Fig. 3).[5]

[Figures 1 and 2 around here]

[Figure 3 around here]

The evidence on technology and employment also suggests that firm innovative activities may have an impact on the composition of jobs, aside from their number, for instance increasing employment both in low skill/wage and high skill/wage occupations (Autor and Dorn; 2013; Goos et al.; 2014). As well documented by Autor and Dorn (2013), the adoption of technologies that displace routine-intensive occupations, such as ICTs, induces job polarisation in local labour markets, increasing skilled labour dedicated to abstract tasks, and unskilled labour dedicated to manual personal services that cannot be routinised. Eeckhout et al. (2014) refer to extreme skill complementarity, which may be driven by the increase in demand for personal services commanded by the increased number of highly-paid abstract jobs associated to the adoption of new technologies (Mazzolari and Ragusa; 2013). Importantly, the larger the initial share of routine intensive jobs in the local labour market, the more pronounced is the polarisation that follows technical change (Autor and Dorn; 2013). Focusing on job multipliers, Lee and Rodríguez-Pose (2016) document that an increase in high tech sectors' employment in the US leads to an increase in the employment of low skilled workers, with no benefits on poverty reduction. In the UK, Lee and Clarke (2017) find that each job in a high tech sector creates 0.9 jobs in non-tradeable services, 0.6 of which go to low skilled workers, all in poorly paid occupations. Autor and Salomons (2018) provide new empirical evidence on the the effect of productivity growth on employment across EOCD countries for more than 35 years. They document that, within industry, productivity growth is associated with a reduction in employment, but aggregating at the economy level, an increase in employment is observed, especially in

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[4]See below for the estimation strategy and the definition of routinised occupations.

[5]A part from unemployment, these patterns seem persistent, suggesting that a structural phenomenon might be at work (Haldane; 2017a). They also disguises a substantial degree of spatial polarisation (Haldane; 2017b,a), which, among other things, may be attributed to sectoral and geographical agglomeration of activities (Powell et al.; 2002; Echeverri-Carroll and Ayala; 2009; Meliciani and Savona; 2014) that have an effect on labour market dynamics (Korpi; 2007; Matano and Naticchioni; 2011; Berger and Frey; 2016).

services. Their results point to a compensation mechanism where lower prices in sectors with higher productivity increases the demand for business and personal services, which absorbs more workers than those replaced by machines.

To summarise, innovation – measured as growth in high tech sectors jobs, adoption of ICTs, or increase in TFP – has a positive effect on employment, as already noticed, but also changes its composition. While Autor and Salomons (2018) do not study which kind of new jobs are created, the studies focusing on local labour markets suggests that a substantial share of the new jobs are in routine intensive, low paid, personal services (Autor and Dorn; 2013); or more in general low skill, poorly paid, occupations (Lee and Clarke; 2017).

The second contribution of this paper is then to study the impact of R&D on the composition of employment. We first study the impact of R&D investment on the share of workers by levels of education (skill biased technical change) and sector of employment (directly or indirectly related to R&D activities). We then estimate if R&D contributes to the unprecedented increase in self-employment in the UK (Fig. 3 and Haldane (2017b)) and alternative work arrangements (Katz and Krueger; 2016), inducing changes in the type of employment in the local labour market, distinguishing between paid employment and self-employment. Because self-employment may be both an indication of workers picking up innovation opportunities, as well as workers seeking refugee from unemployment in low skill personal services (e.g. driving a car or walking a dog), we distinguish between several types of self-employed. We also study how these changes in composition differ across age cohorts.

We use confidential firm level data with details of their R&D expenditure from the Business Expenditure on Research and Development (BERD) to estimate R&D expenditure per worker at the level of the Travel-To-Work-Area (TTWA), which are local labour markets in the UK. Given the design of BERD, we conservatively focus on large companies' R&D. We combine this with information on the TTWA population in 2001 and 2011 using the respective censuses from the Office of National Statistics (ONS). We combine information on employment and occupation, by sector, age, education, and type of employment. Differently from existing surveys, which are representative at the national level, the census allows to estimate employment figures that are representative at the TTWA level. We distinguish between TTWA that have a share of workers in routinised occupations above the median share (high routinised areas, HRA), from TTWA whose share is below the median (low routinsed areas, LRA). We estimate the impact of a change in R&D in the manufacturing sector in a given TTWA, on the change in employment for different categories of workers, distinguishing between HRA and LRA. To identify the impact of R&D change, we use two instruments that exploit the local industrial specialisation, and sector's propensity to invest in R&D and and exposure to trade. First, we instrument R&D with the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D (Bartik; 1991; Baum-Snow and Ferreira; 2015; Moretti; 2010). Second, holding on the local industry structure, we instrument R&D with the predicted change in a TTWA based on the US industries exposition to Chinese imports in 2001 (Bloom et al.; 2016). Results are remarkably consistent across the two instrumentation strategies.

We find that growth in business R&D investment in a local UK labour market, *ceteris*

paribus, does not affect the ratio of employed and unemployed. On balance, R&D investment growth does not seem to have a multiplier effect on employment. When we distinguish by the initial occupational composition, we find a positive effect of R&D on employment only in areas with high initial shares of workers in routinised occupations.

When we investigate how the composition changes in the different areas, we find that R&D, as expected, increases the share of well educated workers. However, this is not the cases in areas with high shares of workers in routinised occupations, where the share of less educated workers increases, as an outcome of local R&D growth. Significant differences also emerge with respect to the sectors in which R&D tends to push the specialisation in the different areas. On average, R&D has a positive impact on employment in manufacturing, transport and business and financial services, while reducing employment in construction, trade (wholesale and retail) and food and accommodation services. When we focus on RTA, though, we find a positive impact of R&D on all services (including those under retail and accommodation), and a contemporary reduction in jobs in manufacturing, which supports the polarisation driven by extreme skill complementarity.

Distinguishing the impact between paid employment and self-employment, we find that, on average, R&D growth increases the number of workers that have a paid job, with respect to those that rely on self-employment, mainly due to a drop of self-employed workers. Once more, areas with high shares of workers in routinised occupations show a different trend, with self-employment growing faster than paid employment, particularly for age cohorts 16-24 and 25-34. Workers aged 16-24 in areas with high shares of workers in routinised occupations experience a dramatic reduction in paid employment, and no increase in self-employment, while workers aged 25-34 in areas with high shares of workers in routinised occupations experience some increase in paid employment, but mainly move to self-employment; finally, those aged 35-64 see a similar increase in paid employment and self-employment. The most vulnerable cohort is the youngest one; the cohort that gains most from R&D growth is the oldest, which experiences an increase in both paid employment and self-employment; while the middle one seems to venture most in self-employment opportunities.

When we qualify the type of self-employment being created as a result of R&D growth in RTA, we do not find significant differences, among those with and without employees, part-time or full-time. However, Faggio and Silva (2014) document that the increase in self-employment in the UK is correlated with firm formation and innovation only in urban areas, whereas in rural areas it is more related to the lack of employment opportunities. If areas with high shares of workers in routinised occupations are prevalently rural, the shift from paid employment to self-employment as a result of R&D growth may be a sign of a negative effect on the labour market, which raises personal service occupation in the form of self-employment, especially in service sectors. More research in studying the self-employed is needed.

It should be noted that, because areas with high shares of workers in routinised occupations are less populated (15% of the UK population in total), the different impact that R&D has in these areas, never predominate on the average effect across the UK.

The remainder of the paper is structured as follows. Section 2 briefly reviews the rel-

evant literature and discusses the rationale for focusing on R&D. Section 3 details the data used and their combination. Section 4 discusses the estimation and identification strategies. Section 5 discusses the results, while Section 6 summarises the main findings.

2 Theoretical Background and Literature

2.1 State of the Art and New Challenges

Old and new theories have not come yet to uncontroversial empirical explanations of how technical progress affects labour. This is also due to the use of different theoretical frameworks, combined with different proxies for innovation, and units of analysis.

One influential theoretical framework, the skill-biased technical change (SBTC) hypothesis (Acemoglu and Autor; 2011; Saint-Paul; 2008), predicts that if innovation increases the demand for skilled labour and skills are slow to adjust, the excess of supply of unskilled labour and the low supply of skilled labour may trigger employment polarisation. But his framework considers innovation as an exogenous event, and distinguished workers in terms of skills, which can be used in any occupation.

This theory has recently incorporated evidence on mid-skill jobs growing comparatively less than high- and low-skill ones (Autor et al.; 2003a, 2005). The routine-replacing technical change (RRTC) framework (Autor and Dorn; 2013; Goos et al.; 2014; Van Reenen; 2011) explains this recent evidence on employment polarisation with the increased automation of works commanding routinised tasks. This is often discussed with reference to the adoption of specific technologies, such as ICTs, which may replace specific types of tasks, particularly those easier to routinise and therefore to replace with machines. The main factors accounted for in this framework are the initial (task) specialisation in local labour markets, which determines the rate of adoption of technologies expected to replace specific tasks and the extent to which dismissed jobs are then re-employed in local lower-skilled occupations.

Classical economists have proposed several compensation mechanisms, through which workers that are made redundant by specific technologies may be employed in other occupations.[6] The theory identifies different mechanisms, distinguishing between product and process innovations. Process innovation is intrinsically aimed at saving labour costs and therefore is job-displacing – such as automation (Brynjolfsson and McAfee; 2012; Frey and Osborne; 2015). However, new jobs may be created as: increased productivity may reduce prices of the final goods, thus increasing demand; reduced wages may induce an increase in labour demand – as for example in the context of the current recession in the UK (Pessoa and Van Reenen; 2014); investment from extra profits may be invested, generating new jobs; increased wages linked to productivity growth may increase demand (Pessoa and Reenen; 2013). Product innovation might instead be job-creating through diversification and increased variety (Chai and Moneta; 2010), provided that new products do not completely displace obsolete products.

Harrison et al. (2014) test for the resulting outcome of the compensation mechanisms

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[6]For a review, see Calvino and Virgillito (2018) and Piva and Vivarelli (2017).

at the firm level, exploiting innovation surveys that ask firms about different types of product and process innovation, following the Frascati Manual (Community Innovation Survey, CIS). They study firms across France, Germany, Spain and the UK for 1998-2000. They find that innovation overall has a positive effect on employment, at the firm level. In particular, process and productivity increasing innovations may replace employment, but price reduction overcompensate inducing an overall positive impact on employment. The strongest positive effect is due to product innovations, which create new demand, beyond stealing jobs from competitors. Similar result were reported across several countries using similar indicators of product and process innovation (see Calvino and Virgillito (2018) for a review). Similar results were also found, at the firm level, extending to R& expenditures (Bogliacino et al.; 2012) and patents (Coad and Rao; 2011). Autor and Salomons (2018) do not tests for compensation mechanisms, but they also find that reduction in within industry employment related to an increase in TFP, in 19 OECD countries over more than 35 years, is overcompensated by an increase in employment in other industries.

Theory from economic geography predicts that innovative areas may bring a wage and employment premium, attracting jobs, investment and firms (Hornbeck and Moretti; 2018). The theory is based on agglomeration economies (Feldman and Kogler; 2010; Glaeser and Maré; 2001; Meliciani and Savona; 2014; Mion and Naticchioni; 2009) dating back to Marshallian externalities. The evidence tends to focus on high tech sectors and productivity growth as indicators of innovation. Moretti and Thulin (2013) build on the job multiplier theory (Moretti; 2010) to estimate the impact of an increase in one job in a high tech sectors, in a local labour market, on the number of jobs created in other non tradeable sectors. Jobs created in a local labour market in a high tech sector create up to six additional jobs, in services, once controlling for local prices, wages and services. Educated workers gain most. A smaller, but still positive multiplier is found by Lee and Clarke (2017) for UK local labour markets. In their case, those who gain most are the unskilled workers. Gagliardi (2014) takes a different approach and indicator, closer to what we also do in this paper. She studies the impact of innovation on local labour markets exploiting the local industry specialisation. As an indicator of innovation she uses patents (to account for actual outputs, rather than inputs) She finds that innovation is negatively correlated with employment (reduces employment), and the effect is stronger in areas with mature industries. Workers with intermediate skills are the most affected. She also finds that areas that attract more skilled workers also attract less skilled workers, as the former generate employment in low skill services.

With the exception of the RRTC framework (Autor and Dorn; 2013), these studies focus on the level of employment, at firm, local, or industry level, irrespective of the indicator used. However, most of them implicitly suggest that labour created may be different from the labour replaced by innovation (e.g.in Autor and Salomons; 2018). For instance, a number of studies document the role of innovation in increasing local inequality (e.g. Aghion et al.; 2015; Echeverri-Carroll and Ayala; 2009; Lee and Rodriguez-Pose; 2012). Lee and Rodríguez-Pose (2016) explicitly investigate the kind of labour that is created by an increase in high-tech industries employment shares. They find that across US local labour markets, high tech employment increases employment and wages, also for low educated

workers, they have no positive impact on reducing poverty. Lee and Clarke (2017) study which kind of jobs are created in UK local labour market by an increase in high tech employment shares. They also find a positive job multipliers, mainly on low skilled workers, but the new jobs are poorly paid and are mainly in services.

2.2 R&D and Employment

As discussed, with the exception of firm level studies on the compensation mechanisms, earlier studies tend to proxy innovation with (tangible) capital investments, such as ICTs (Autor and Dorn; 2013; Brynjolfsson and McAfee; 2014; Michaels et al.; 2014; Van Reenen; 2011), more recently advanced automation and industrial robots (Acemoglu and Restrepo; 2017; Arntz et al.; 2017; Frey and Osborne; 2017; Graetz and Michaels; 2015), or patents (Aghion et al.; 2015; Gagliardi; 2014).

Tangible investments in new capital are a crucial source of innovation, usually referred to as embedded innovation, but do not offer new ideas, products, or processes, that may be exploited in further innovation processes in the rest of the economy, to the same extent of R&D. In the neverending debate on the pros and cons of different innovation indicators (Kleinknecht et al.; 2002) patents capture (potential) new products, and tend to be more reliable in measuring innovation output, given that non all R&D is patented. However R&D may lead to different forms of innovation, with important consequences on employment generation. The non linearity in the relation between R&D expenditure and patents may be due to differences across industries in innovation opportunities and the appropriability of technology (Breschi et al.; 2000); the industry life cycle (Klepper; 1996); the choice of different instrument to appropriate innovation rents (Pajak; 2016); or the use of patents as a defensive strategy (Gilbert and Newbery; 1982).

While patenting firms are likely to perform R&D at some stage, not all firms investing in R&D patent. The use of patents as a proxy for technical change in this context might therefore risk to underestimate the effect of an investment in innovation on employment. R&D allows the creation and adoption of new technologies in production processes, and of marketable novel applications, which ideally increase firms' market shares and knowledge stock (Freeman and Soete; 1987; Freeman et al.; 1982).[7] R&D captures innovation effort and thus the resources – including labour – that the firm commits to innovation even before the innovation is realised. Investment in R&D may substitute or complement alternative inputs such as capital and other forms of labour (unrelated to R&D).[8]

Depending on the initial local industrial structure (Gagliardi; 2014) and skill composition (Autor and Dorn; 2013), R&D may increase the demand for skilled workers – as predicted by the skill biased technical change literature – especially in manufacturing high-tech sectors, and related personal services, as predicted by Eeckhout et al. (2014). R&D

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[7]In the internationally agreed standards defined by the Organisation for Economic Cooperation and Development (OECD) Frascati Manual, R&D is defined as "creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society and the use of this stock of knowledge to devise new applications." The basic measure is 'intramural expenditures', that are all current and capital expenditures for R&D performed within a statistical unit (firm) or sector of the economy.

[8]R&D investments are of a composite nature and entail resources that are devoted to specific high-skill workers who performs creative tasks such as basic and applied research, but not all high-skilled workers such as scientists and engineers perform R&D (Barth Erling and Wang (2017)), although they may well be complementary to it.

investments in areas with highly specialised skilled workforce may attract more skilled workers, to work in the R&D activities, and in related spin-offs. If the R&D growth occurs in areas with highly routinised labour, though, this may have a negative effect on the demand for local employment, which do not have the skills to work in the new jobs commanded by R&D investments. However, the inflow of skilled labour might spur demand for complementary (routinised) tasks to be performed by lower-skill workers (Autor and Dorn; 2013; Mazzolari and Ragusa; 2013).

2.3 Local Labour Markets, R&D, and Self-Employment

Self-employment has increased dramatically in the UK since 2000 (Fig. 4 and Haldane (2017b)), and alternative work arrangements represent the bulk of the US employment growth over the last few years (Katz and Krueger; 2016). The Gig Economy has shown an upward trend of self-employed in the UK (Adams et al.; 2017). Gigged workers deliver low skill tasks – mainly services – through the use of digital platforms with unprecedented time flexibility (Kenney and Zysman; 2016).

As argued above, a firm increasing its R&D investments may recruit for specific abstract tasks as well as complementary tasks. On the one hand, if R&D brings also process innovation, some of the current jobs may become obsolete – increasing unemployment. On the other hand, R&D may create spillovers (Feldman and Kogler; 2010), in the form of opportunities that may be captured by new businesses. In both cases R&D generates incentives for workers to seek a better opportunity with respect to the current situation by moving to self-employment (Blanchflower and Oswald; 1998): either to exploit the opportunities (Bloom et al.; 2013), or to cope with unemployment (Thurik et al.; 2008).

Whether R&D nurtures one or the other type of entrepreneurship depends on the skill mismatch (Åstebro et al.; 2011; Vona and Consoli; 2015) between local workers and the jobs created by R&D, and on the local industry specialisation, particularly the technological regimes of each industry (Breschi et al.; 2000). The initial employment structure and the availability of a pool of specific skills within a local labour market is likely to play a crucial role in the net effect of innovation on paid employment. If local workers have been trained mainly in occupations with highly routinised tasks, they will not be able to apply for jobs that require mainly abstract skills related to R&D investments. These workers will have a better chance to offer personalised services to those who are employed in R&D related activities (Autor and Dorn; 2013). These are likely to come in the form of self-employment, such as driving an Uber car. Without proper retraining programmes, these workers characteristics are likely to be path-dependent: workers will have a low probability to move to better occupations: there more so the more the gap between their skills and those demanded by R&D related occupations widens. For instance, (Levine and Rubinstein; 2017) distinguish between incorporate and unincorporated self-employment: they document that while incorporated self-employed is usually associated to increases in non-routinised workforce, unincorporated self-employed makes use of relatively higher routinised workforce. As a result, the larger the initial share of routinised workers, the higher the probability that they will seek refugee in self-employment activities related to R&D, and its spillovers, when the investment increases.

Technological regimes (Breschi et al.; 2000) influence the relation between industrial dynamics and innovative activities. Technological opportunities define the likelihood of innovating for a given investment: the higher the opportunities, the lower the risk of not succeeding for new ventures. Appropriability defines the degree to which an innovation can be imitated: the higher the appropriability, the lower the probability to imitate an innovation, the higher the rents for the innovator and the lower the incentive for new ventures to innovate in the same area. Cumulativeness defines the degree to which earlier innovation are necessary to innovate in the same area: the higher the cumulativness, the higher the advantage of those who have innovated in the past and appropriate the knowledge and technology related to the innovation, and the lower the incentive for new ventures to innovate in the same area. Technological regimes may then predict the likelihood that innovations, in a given industry, occur mainly as a result of R&D investments in labs of large incumbent firms – industries with low opportunities, high appropriability and cumulativeness, or as a result of new firms entering the market with new products and processes. In the first case, we tend to observe high concentration, low spillovers, and low entry of new firms. While in the second case we tend to observe lower concentration, higher spillovers, and higher entry of new firms. As a result, depending on the technological regimes of the local industries, we may observe more or less workers opting for self-employment to exploit some of the opportunities related to R&D investment.

The initial degree of routinisation of the local labour force and the industry specialisation (technological regimes) may then determine the type of self-employment generated by R&D investment growth, if any.

As noticed, self-employment in the UK has increased substantially in the UK in the last two decades, but the share of those who hired other workers has decreased (Fig. 5 and Haldane (2017b)). Coad et al. (2017) show that self-employed who hire one more worker tend to be entrepreneurs seeking for opportunities (rather than refugee from unemployment). Blundell et al. (2014) refer to the post recession increase in self-employment as "hidden unemployment", with an increasing proportion of self-employed who earn less than paid employees. In relation to innovation, there is only one study that we know of that studies the characteristics of self-employed in the UK and their relation with innovation opportunties. Faggio and Silva (2014) study the relation between self-employment (distinguishing between managers, owning a business, and freelancers), firm entry (gross rate, number of new firms in a given year, net rate of entry, birth minus death as a share of existing firms), and firm innovation (measured from the CIS) in local labour markets. They find that most measures of self-employment are correlated with gross and net entry of firms, as well as with inventive activity. But this relation is significant mainly in urban areas, whereas in rural areas self-employment seems to be related manly to the lack of employment opportunities.

To sumamrise, innovation can be disruptive by creating new entrepreneurial opportunities and/or unemployment. Both job redundancies and entrepreneurial opportunities depend on the industrial and employment composition that characterise local labour markets. The UK typically presents a substantial degree of spatial heterogeneity, with (rural) areas specialised in mature manufacturing characterised by a high share of rou-

tinised workforce and (urban) areas dense in knowledge intensive business services that employ non-routinised workforce. In this paper we investigate the impact of R&D on the type of employment, distinguishing between paid employment and self-employment. And we then study the type of self-employment generated, distinguishing between part/full-time and with/without employees.

3 Data

We combine different data sets to generate variables on employment status and R&D investment at the level of the Travel-to-Work-Area (TTWA) in the UK. We use data from the population census to construct labour outcomes. The primary source for the census data is the Office of National Statistics (ONS), but we use the census aggregates elaborated by the UK Data Service[9] and NOMIS[10].

We include 212 TTWAs from England, Scotland and Wales that we observe in two periods, 2001 and 2011.

From the census we also retrieve information on the occupational categories that we use to define areas with a high share of workers in routinised occupations (HRA). The NS-Sec classification distinguish between seven categories: higher managerial and professional occupations, lower managerial and professional occupations, intermediate occupations, small employers and own account workers, lower supervisory and technical occupations, semi-routine occupations, and routine occupations. We calculate the share of labor accrued by *routine occupations* in every TTWA in 2001. Figure 6 plots this share. In 2001, the south of Britain had the lowest routine share, while TTWA in the north had a larger share of routinised employment. The median share across TTWA is 0.13, and is used to define areas with a high share of workers in routinised occupations (HRA), i.e. areas where the share of routinised workers is larger than 0.13.

[Figure 6 around here]

Information on business R&D expenditures is retrieved from the Business Expenditure on Research and Development (BERD) survey administered by the ONS. The survey is a sub-set of the Annual Business Survey (ABS). According to the design of BERD, the survey targets 93% of the 400-500 businesses responsible for 80% of UK business R&D expenditures and follows them every year. For the remaining 20% of UK business R&D expenditure, BERD targets 90%, with an important under-coverage for small businesses: 9.6% for businesses with less than 10 employees (Ker and Greenaway; 2012). Because of this bias in the design, our analysis focuses on the effect of R&D expenditure of large R&D contributors, without making claims about statistical representation for the R&D expenditure of all firms in the UK.

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[9]We use Casweb to retrieve data for the years 1991 and 2001. https://census.ukdataservice.ac.uk/get-data/aggregate-data

[10]For the year 2011. https://www.nomisweb.co.uk/census/2011

We calculate R&D at the TTWA level as the average R&D expenditure per worker within the TTWA. For each year (2001 and 2011) we use three years of data to improve precision. For year t, we use information of all the firms surveyed by BERD in years $t-1$, t and $t+1$, and estimate the following equation using firm's turnout as weight:

$$\ln RD_{fti} = \alpha + \beta \ln Employees_{ft} + \theta_i + \tau_t + \varepsilon_{fti} \tag{1}$$

Where RD_{fti} is the total R&D expenditure of firm f in year t and TTWA i. $Employees_{ft}$ is the number of employees as reported in the Inter-Departmental Business Register (IDBR), τ_t is a dummy variable for each year, and θ_i is a dummy variable for each TTWA. We recover the estimated coefficient $\hat{\theta}_i$ for years 2001 and 2011 that we use to calculate our measure of R&D growth at the TTWA level: $\Delta RD_i = \hat{\theta}_{2011} - \hat{\theta}_{2001}$.

4 Econometric strategy

Our main objective is to estimate the impact of innovation on the changes in the local labour market. Operationally, we employ a set of dependent variables that capture different dimensions of the composition of the local labour market outcomes. These include: employment and unemployment, in different industries, for individuals with high and low level of education, in paid labour and self-employed, and from different age cohorts. For the sake of brevity, y denotes our dependent variables, the measures of different dimensions of employment, while our key explanatory variable, ΔRD reflects the variation in the investment in R&D in TTWA i. The relation between R&D growth and local labour market outcomes is then defined by the following equation:

$$\Delta y_{it} = \alpha + \beta \Delta RD_{it} + \gamma_c + \varepsilon_{it} \tag{2}$$

We take first differences of all variables, ruling out any unobserved fixed effect at the TTWA level.[11] Δy_{it} is the change from 2001 to 2011 of labour outcome y in TTWA i; ΔRD_{it} is the change in R&D expenditure of the average firm in TTWA i. γ_c captures country-specific trends (for England, Scotland and Wales) and ε_{it} is the statistical disturbance.

We are also interested in how the effect of R&D over labour outcomes may vary for TTWAs with different initial degree of routinisation of the labour market. Autor et al. (2003b) and Autor and Dorn (2013), among others, have highlighted the crucial role played by the level of routiniasations of local occupations in explaining employment polarisation following the adoption of ICT. We explore the impact of the initial level of TTWA's routinisation by interacting ΔRD_{it} with ϕ, a dummy variable that is equal to one when the ith TTWA is characterised by an above-median share of workers employed in routine occupa-

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[11]Taking the first differences allows us to eliminate time invariant TTWA-level unobserved characteristics, including – among others – the TTWA idiosyncratic exposure to the 2007-08 global financial crisis.

tions in 2001.[12,13] Formally, we estimate the following equation:

$$\Delta y_{it} = \alpha + \beta_1 \Delta RD_{it} + \beta_2 \phi \times \Delta RD_{it} + \gamma_c + \varepsilon_{it} \tag{3}$$

Estimating equations 2 and 3 with OLS might yield biased coefficients for R&D due to reverse causality, unobserved heterogeneity, and measurement error. First, as discussed in the economic geography literature, innovation may generate spillovers, which may attract skilled labour, which in turn may provide an incentive to invest in innovation activities as it has become more productive. As a result, employment outcomes may influence R&D activities in a TTWA. Second, and perhaps more importantly, there may be unboserved factors not captured in our estimation that may boost both employment growth and R&D growth in a given TTWA. For instance, public investment in R&D, or the presence of universities, may generate employment opportunities and also stimulate R&D in private companies, through collaborations. Finally, measurement error in the reporting of R&D is possible. Respondents may also refer to different lines of spending as part of R&D. Instead, we do not expect the dependent variables (change in employment variables from 2001 to 2011) to affect the level of routinisation in 2001, captured by the dummy variable ϕ.

We address these issues using two Instrumental Variables (IV) approaches. The first exploits the initial compositions of output across industries in TTWA i interacted with the nationwide change in industry R&D (excluding TTWA i). We refer to this first instrument as the shift-share instrument, or Bartik instrument The second approach exploits the accession of China to the World Trade Organization in 2001 and uses the industry exposure of TTWA i to China imports, interacted with the US growth of China imports (as US imports are more exogenous than EU imports). We refer to the second instrument as the trade-induced instrument.

4.1 Shift-share instrument

Here we detail our first instrumenting approach. We use the initial output share of industries[14] in TTWA i to predict i's change in R&D, multiplying the national R&D change (excluding TTWA i) by i's sector shares. In this way we isolate the change in R&D across TTWAs due to changes in nation-wide (excluding TTWA i) dynamics in R&D from shocks in TTWA i that would be otherwise correlated with the TTWA labour outcomes. The source of identification comes from differing base year industry compositions across TTWA. As argued by Baum-Snow and Ferreira (2015), "[t]he validity of this instruments relies on the

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[12]Table 1 lists the top and bottom TTWAs according to their share of workers in routinised occupations in 2001. The average and median share of routinised employment are about 0.13. ϕ is defined as the share of workers in routine occupations in TTWA i over all i's employment. We use the National Statistics Socio-economic classification (NS-SEC) developed by ONS to define routine occupations: NS-SEC 1: Higher managerial, administrative and professional occupations; NS-SEC 2: Lower managerial, administrative and professional occupations; NS-SEC 3: Intermediate occupations, NS-SEC 4: Small employers and own account workers; NS-SEC 5: Lower supervisory and technical occupations, NS-SEC 6: Semi-routine occupations; NS-SEC 7: Routine occupations. ϕ is the share of NS-SEC 7, routine occupations over the rest.

[13]We also check for results including the semi-routinised occupations (NS-SEC 6) to define ϕ as the TTWA above the median share of workers employed in routine occupations. The inclusion of semi-routines occupations does not change our results.

[14]In what follows, we measure the initial output share of industries using turnover. We re-run our estimates using the initial employment share of industries and results are consistent with our main results.

assertion that neither industry composition nor unobserved variables correlated with it directly predict the outcome of interest conditional on controls". It is worth mentioning at this point that the exclusion of the corresponding TTWA in the estimation of the nation-wide change in R&D at the industry level helps us to account for local unobservables that may drive both employment variables and local R&D. Therefore, we use only aggregate variation at the industry level, which is also external to the relevant TTWA.[15]

We proceed in two steps. First we estimate the aggregate changes in industry R&D that will be used to predict R&D at the local level. We estimate the following equation:

$$\ln RD_{fjt} = \alpha + \ln Employees_f + \theta_j + \theta_t + \varepsilon_{fjt} \tag{4}$$

Where RD_{fjt} is the intramural R&D expenditure of firm f, in year t, in industry j; $Employees_f$ is the number of employees in the firm f; θ_t is a year dummy; and θ_j is an industry dummy.[16] We include data for years 2000, 2001 and 2002 to estimate the average R&D firm expenditure in 2001 for the relevant industry. Likewise, we use data from years 2010, 2011 and 2012 to estimate the average R&D firm expenditure in 2011 for the industry level.

The estimated set of coefficients for each industry in each period, $\hat{\theta}_j$ is our measure of average R&D expenditure in the industry. The aggregate change in average R&D expenditure by industry, for the relevant TTWA i, is defined as:

$$\Delta RD_{-ij} = \hat{\theta}_{j,2011} - \hat{\theta}_{j,2001} \tag{5}$$

The subscript $-i$ indicates that we have excluded the relevant TTWA in the estimation of aggregate changes in industry R&D.

The second step requires the construction of the instrument. For each TTWA i we first estimate the share of output by industry j and TTWA i using the 2-digit UK SIC code (2000 version): ω_{ij}. Second, we estimate ΔRD_{-ij}, which is the change in the average R&D expenditure in industry j at national level, excluding TTWA i.[17] We then define the instrument for TTWA i R&D growth as the weighted sum of sector's j R&D weighted by the TTWA industry shares (computed with turnover):

$$z_i = \Sigma_j \omega_{ij} * \Delta RD_{-ij} \tag{6}$$

Figure 7 maps the variation of R&D investment growth between 2001-2011 across TTWAs (as resulting from our IV strategy).

[Figure 7 around here]

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[15]In urban economics this strategy is used to isolate labour demand shocks and is known as "shift-share". It was originally implemented by Bartik (1991) and Blanchard and Katz (1992). Baum-Snow and Ferreira (2015) provide a insightful discussion of the papers that use the methodology. Recent applications of this identification strategy can be found in Hornbeck and Moretti (2018), Notowidigdo (2013), Guerrieri et al. (2013), Notowidigdo (2013), Bartik (2014), and Diamond (2016).

[16]We use 2-digits industry level (i.e. divisions) as classified by SIC 2003.

[17]We estimate the following equation: $\ln RD_{j-it} = \alpha + \ln Employees + \theta_j + \theta_t + \varepsilon_{j-it}$. $\hat{\theta}_j$ recovers the industry average R&D expenditure. We use three years data for each period 2001 and 2011. Finally, $\Delta RD_{-ij} = \hat{\theta}_{-ij,2011} - \hat{\theta}_{-ij,2001}$

4.2 Trade induced technical change instrument

Here we detail our second instrumenting approach. This strategy exploits the increase in Chinese imports in the US following China's accession to the World Trade Organization in 2001, and their variation across industries. Following Bloom et al. (2016), we expect that increased competition in industry j pushes firm's efforts to become more competitive by increasing innovation through R&D expenditures.

To construct an instrument, Z_i at the level of the TTWA i, we build a measure of UK industries exposure to Chinese trade, proxied by US sectors exposure to make it exogenous. We multiply the j's sector change in US imports by j's share of UK imports from China, weighted by j's share in TTWA i. Formally, we estimated the following equation:

$$Z_i = \Sigma_j \left[\omega_{ij} \times \eta_{ij} \times \Delta M_{jt}^{USA} \right] \tag{7}$$

where ω_{ij} is the employment share of industry j within the TTWA i; η_{ij} is industry j's share of UK imports from China in 2001; ΔM_{jt}^{USA} is the log change (2011-2001) in import for industry j in the USA.

To construct the China import share by industry η_j and the change in US imports from China at the industry level, ΔM_{jt}^{USA}, we used data from comtrade. We aggregated data from comtrade to the Standard International Trade Classification (SITC) level, and then matched these data to the UK 2003 SIC codes. To construct industry employment share (ω_{ji}) we use employment data from the Business Structure Database (BSD).

Finally, in the IV procedure we estimate $\Delta RD_{it} = \alpha + Z_i + \varepsilon_{it}$, and use the predicted average expenditure, $\Delta \hat{RD}_{it}$, in equations 2 and 3.

5 Results

5.1 The Effect of R&D Investment on the Level of Employment

Table 4 reports the baseline estimates of the average impact of R&D investment growth on employment levels across TTWAs over the period 2001-2011.[18],[19] We find that a 10% increase in R&D per employee, for the average TTWA, leads to 0.9% reduction in population (col. 1, panel a), 0.8% reduction in employment (col. 2, panel a) and 1% reduction in unemployment (col. 4, panel a). The impact on the three measures are of similar magnitude, suggesting that R&D leads to a decline in the working population in the same proportion for employed and unemployed, leaving the rate employed/unemployed unaltered (non significant coefficient in col. 6, panel a). As a result, the impact of R&D on the change in employment rate (col. 3, panel a) and unemployment rate (col. 5, panel b) are also not

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[18]Table 3 reports the results of the first stage estimation for both IV strategies: shift-share (col. 1) and trade induced (col. 2). Both instruments are valid, with an F statistics (respectively 123.8 and 164.7) well above the standard threshold.

[19] Across tables, the two IV strategies yield almost identical results, with the exception of the first two tables, which present small differences, that do not change the interpretation nor the economic effect of R&D growth on employment dynamics. We thus show results from both IV for the first two tables, and then focus on our main IV (shift-share IV).

significant.[20]

[Table 4 around here]

From 2001 to 2011 the average TTWA increased its population by 7.8%, employment by 14.4% and unemployment by 44%. These changes across TTWAs are evidence of an important geographical re-shuffling of the UK population (including migration to/from other countries). Our estimated effects of R&D on population, employment and unemployment as proportion of the mean are 11.5% for population, 7.6% for employment and 2% for unemployment. Within a spatial equilibrium setting, these results suggest that R&D growth explains an important part of the labour mobility within the UK between 2001-2011. The reduction in population in high R&D growth TTWAs (with respect to the average TTWAs) may be due to the unequal effect that an increase in productivity has on local labour markets between wages and capital (rents) (Hornbeck and Moretti; 2018). As house rents increase more than wages, low paid workers may be better off moving to a TTWA with less innovative opportunities, lower wages, but proportionally lower leaving costs.[21]

On balance, we find that R&D investment growth, *cæteris paribus*, does not seem to have a multiplier effect on employment. This result differs from what has been found in the literature when estimating the impact of job growth in high tech sectors – which have a positive effect on employment, and the impact of innovation measured as patents in the UK – which is found to reduce employment rates. We seem to find that R&D lays in between the two effects. This may be due to two relevant aspects of considering R&D expenditures. On the one hand, estimating the impact of R&D we explicitly take into account the jobs in R&D activities (which in our data amount to around 60% of business R&D expenditure). On the other hand, the number of jobs created by R&D must represent only one portion of those created by high-tech sectors overall (which compound all occupations, not only related to R&D). These, together with the spillovers that R&D is expected to generate, do not seem to have a multiplier effect: if anything, for the number of jobs created, there is an equivalent number of jobs that are destroyed,as a result of the increase in R&D.

How does the effect of R&D differ when we consider the initial level of routinisation of the workforce? To investigate the role of the initial composition of occupations we distinguish between TTWAs with an initial high (HRA) vs. low (LRA) share of workers in routinised occupations.[22]

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[20]The trade induced instrument suggest a smaller impact of R&D on employment (col 2, panel b) with respect to unemployment (col. 4, panel b), resulting in a significant positive impact on the employed/unemployed ratio of 0.4% (col 6. panel b). The magnitude of the economic impact is quite similar.

[21]However, the negative impact on population, employment and unemployment may be due to an outmigration of both unemployed and employed in equal proportions, an outmigration of unemployed twice the size of the increase in unemployment, or any other combination of individuals moving across employed and unemployed status and across TTWAs. Census data unfortunately do not allow to study which combination prevails, and the comparison with micro data – Such as the British Households Panel Survey (BHPS) – did not deliver results comparable with the census data. Moreover population dynamics is the result of migration across TTWAs, as well as migration to and from other countries. Results may also indicate that TTWAs experiencing higher R&D growth attract less migrants, with respect to TTWAs with low R&D growth. If most migrants are low skilled, this is an expected result.

[22]In terms of population, TTWAs with low initial routine share account for 85% of the population, while TTWAs with a large share of routinised employment account for 15% of the population. Most people live in low-routine areas (as measured in 2001).

Table 5, panel a, shows that the effect of R&D on employment differs across HRA ($\phi = 1$) and LRA. In LRA, when we instrument R&D with the initial industrial specialisation, only the population effects remains significant: R&D reduce population (col. 1) and the number of employed (col. 1) at the same rate, with no effect on employment rates (col. 3). This means that LRAs where R&D grows rapidly are less attractive than less innovative LRA. This may be due to the increasing costs of those TTWAs (Hornbeck and Moretti; 2018).

In HRA the negative impact of R&D on the population is lower (col. 1), employment grows more than in non innovative HRA (col. 2), and unemployment falls significantly more than in non innovative HRA and than in innovative LRA (col. 4). As a result R&D has a high net employment multiplier in HRA (col. 6). This may suggest that R&D investment is more attractive, for the average worker, when in occurs in HRA than in LRA

[Table 5 around here]

When we instrument R&D with the import competition from China (Table 5, panel b) results are unchanged for HRA, but differ for LRA. In these areas, an increase in R&D related to an increased trade competition has a significant negative effect on employment, and a significant positive effect on unemployment, which result in a net decrease in the ration of employed and unemployed, when purifying for changes in the population.

5.2   The Effect of R&D Investment on the Composition of Employment

Industry

To investigate what kind of employment is created by R&D in routinised local labour markets and whether the lack of positive multiplier in non-routinised local labour markets hides a change in composition, we first disentangle this effect by sector of activity (industry). Table 6 reports the estimates of the overall effect of R&D investments on employment for each industry (Panel a) and the effect distinguishing by degree of routinisation of the TTWA (Panel b).

[Table 6 around here]

We find that R&D investment has an overall positive multiplier effect on local employment (panel a), but this is limited to some industries, and is compensated by a reduction in other industries. In particular, employment grows in manufacturing (col. 1), transport (col. 3), and to a small extent in business and financial services (col. 5), and shrinks in non tradeable services such as construction (col. 2), retail, accommodation and food (col. 4) and the public sector (col. 6).[23]. Overall, for R&D investment we do not find the extreme skill complementarity that is observed in the case of the adoption of machines and

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[23]Labour composition across sectors is reported in table 2

the increase in skilled labour (Autor and Dorn; 2013; Eeckhout et al.; 2014; Mazzolari and Ragusa; 2013), despite the evidence that R&D increases labour with higher education, as we discuss below.

When we distinguish by initial level of routinisation (panel b), the effect of R&D growth on employment in HRA differs significantly from the overall effect. First, there is a strong reduction in manufacturing jobs (col. 1): a 10% increase in R&D reduces manufacturing jobs in HRA by 11%. This is offset by job creation in all service sectors (a part from public services). A 10% increases in R&D over 2001-2011 increases employment in construction by 30% (col. 2), in retail, accommodation and food services by 27%, and in business and financial services by 59%.[24]

Results suggest that of R&D investment growth triggers de-industrialisation (or tertiarisation) in areas which were dense in highly routinised jobs. Results are also in line with the evidence on polarisation and extreme skills complementarity (Autor and Dorn; 2013; Eeckhout et al.; 2014; Mazzolari and Ragusa; 2013): we observe a similar growth in high skilled services, such as finance and business services, and in low skilled services, such as retail accommodation and food, where most of the personal services are included.

These results complement the available evidence on the complementarity / substitutability of routinised jobs and technological change (Autor et al.; 2003b; Goos and Manning; 2007, e.g.), pointing to important implications in terms of structural and sectoral transformations induced by innovation. In local labour markets where technological change has not led to a strong replacement of routinised jobs yet, further innovation investments trigger a de-industrialisaiton process, which does not occur – and in fact is reversed – in areas that have been already subject to a reduction of routinised employment.

Education

Next, we turn to the composition of employment created by R&D investment in terms of workers' education. Table 7 reports the estimates of the overall effect of R&D investments on employment for high and low educated workers (Panel a) and the effect distinguishing by degree of routinisation of the TTWA (Panel b).[25]

[Table 7 around here]

Overall, we find that R&D growth increases the number of highly educated workers, relative to low educated, especially in LRA. This is well explained by the SBTC theory. Distinguishing also by initial routinisation, we find that in HRA R&D induces an increase in the number of low educated workers, in relation to highly educated workers.[26] This is counterintuitive and cannot be explained by the SBTC framework, but is line with the

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[24]Unfortunately, census data do not allow to distinguish between knowledge intensive business services from other business services.

[25]Highly educated include those who have attended school until level 4 or more for England and Wales, and levels 3 or above for Scotland (equivalent to a higher national certificate). Low educated are all other workers who have attended school till a lower grade than the highly educated.

[26]HRA represent only 15% of the UK population: therefore the overall effect of R&D increases the ratio of highly educated with respect to low educated.

mechanisms discussed in the RRBT framework, as we discuss below.

Taking together the results so far, R&D in LRA has no impact on employment levels, but changes the composition towards more educated workers in manufacturing industries. Instead, in HRA R&D growth has a positive impact on employment levels, but changes the composition towards less educated workers, mainly in non tradeable and personal services, although also financial and business services increase. Overall, employment moves away from manufacturing industries.

Results suggest that in LRA the effect of R&D is concentrated on manufacturing, high-educated employment, whereas the low-educated employment created in HRA is most likely concentrated in non-tradable services. These results suggest that the spatial heterogeneity in the UK in terms of initial employment structure of local labour markets is responsible for a substantial part of the polarisation effect of R&D in terms of sectoral structural transformation.

5.3   The Effect of R&D on Paid Employment and Self-Employment

Depending on the initial composition of skills and industries (technological regimes), the effect of R&D on local labour markets may also be related to the decision of individuals to seek technological opportunities or take refugee in self-employment. Table 8 reports the estimates of the overall effect of R&D investments on paid employment and self-employment (Panel a) and the effect distinguishing by degree of routinisation of the TTWA (Panel b).

[Table 8 around here]

We find that, on average, an increase in R&D reduces both paid employment and self-employment (Cols. 1 & 2), but the effect is stronger on self-employment, resulting in an increase in the ratio between paid employment and self-employment (Col. 3). Results suggest that the reduction in employment that is entirely absorbed by a reduction in population (Table 5), is driven by self-employed which are not attracted to areas with high R&D growth. This seems to suggest that, across the UK, R&D doe snot seem to create opportunities for entrepreneurs, which seems to suggest that the specialisation in the average TTWA is characterised by sectors that appropriate innovations, gain from past investments in R&D, and offer few opportunities for new entrants.

Once again, the effect is significantly different in HRA, where R&D growth also reduces the number of workers in paid employment (col. 1), but has a strong and positive effect on the number of self-employed (col. 2), resulting in an increase in the ratio between paid self-employment and paid employment (Col. 3). As discussed above, this may be due to the fatc that in HRA there are more entrepreneurial opportunities as a result of the growing local R&D activities (which would also explain the lwoer reuction in population), or to the fact that R&D creates skills mismatches, leading individuals to resort to self-employment as an alternative to unemployment. We make a first attempt to answer this question below,

after complementing the evidence of R&D on paid employment and self employment with age differences.

Distinguishing by age cohorts we also find that in HRA the ratio of self employed over paid employed increases mainly for younger cohorts, especially those between 16-24.

To investigate which cohort is most likely to be affected by R&D, we distinguish the impact of R&D growth by age cohorts, for both paid employment and self employment (Table 9), and distinguish between HRA and LRA. We find that, on average, R&D reduces paid employment (panel a) mainly for the middle cohorts (25-34) (col. 2), whereas the youngest (16-24) increase their presence in the (paid) labour market only marginally (col. 1) and it exerts no effect on the oldest cohort (35-64) (col. 3).With regard to self-employment (panel b), R&D reduces their number across the board, although the strongest impact is on the middle cohort (25-34) (col. 2), and the lightest is on the oldest cohort (35-64) (col. 3).

[Table 9 around here]

As in all previous results, the effect of R&D growth depends on the initial workforce composition. Focusing on HRA we find that R&D growth has a negative impact mainly on the youngest cohort and a positive impact mainly on the older cohorts. In particular, we find that in HRA, the youngest cohort (16-24) lose jobs as a result of R&D growth (col. 1, panel a), and experience no increase in self employment (col 1, panel b). The large increase in self-employment in HRA, which we we discussed above, is mainly concentrated in individuals between 25 and 34 years old (col 2, panel b). Individuals in this cohort, though, seem to loose paid jobs, similarly to age peers in LRA (col 2, panel a). Finally, older cohorts (35-64) in HRA gain from R&D both in paid employment (col 3, panel a) and self-employment (col 3, panel b).

Qualifying the Effect on Self-Employment

From the above results self-employment emerges as an alternative occupational choice engendered by growth in R&D investment in HRA. Because this can be due to individuals exploiting new opportunities leaked form the local R&D, or to individuals that have lost their job, because of R&D, we investigate the type of ventures that are created in different TTWAs. We know that mainly individuals between 25-34 move from paid employment to self-employment, although older cohort also increase the number of self-employed as a consequence of R&D growth.

Table 10 reports the estimates of the overall effect of R&D investments on different types of self-employment, distinguishing between part-time and full-time and self-employment with and without employees (Panel a), and distinguishing also by degree of routinisation of the TTWA (Panel b).

[Table 10 around here]

Results neatly confirm that, on average, R&D growth reduces the number of self-employed individuals. This is driven by what happens in LRA. Self-employed, instead, increase as an outcome of R&D growth in HRA. However, we fail to find significant differences among different types of self-employed, especially with and without employees. A 10% growth in R&D increases self-employed with employees by 18% and self-employed without employees by 37% but the difference is not statistically significant. Similarly, among the self-e,ployed with employees there is a larger increase among those part time, but the difference is again not significant.

Overall, we could find no evidence whether the increase in self-employment is associated to an increase in opportunities related to the R&D increase, or to a coping strategy of those individuals who loose their paid job due to R&D.

6   Conclusions

The extant literature has shown that innovating firms benefit from a net growth in employment. Moving to labour markets, technological change in the form of increased jobs in high tech sectors, adoption of ICT, and increase in TFP, tends to exert a positive impact on employment at the local and/or national level. Only industrial robots and patenting activity seem to suggest an opposite impact on local jobs. The literature has also investigated changes in the composition of employment, focusing on skills and type of occupation (measured by share of routinised tasks, wage, or sector).

This paper adds to this evidence in several ways. First, we measure innovation in a comprehensive way, focusing on the intention of the firm to innovate: investment in R&D. We discuss the advantages, and limits, of referring to an indicator that captures firm innovation strategy, which also requires a choice in terms of resource allocation. Second, we account in the same empirical setting for two conditioning factors that are usually considered separately in the literature: the local industrial structure and the occupational composition by routine intensity. Third, we dig into the types of employment that are created by R&D, in an attempt to uncover its main impact. Fourth, among those decomposition we extend the analysis from paid employment to self-employment, and we make a first attempt to study whether the self-employment generated is due to the opportunities leaked by R&D, or by the need to substitute for lost employment.

All the analysis is done at the level of local labour markets in the UK (Travel-to-Work-Areas), exploiting the information from the census in 2001 and 2011, which is representative at the TTWA level. We use two IV strategies, exploiting the local industrial specialisation and its relation to the national level R&D expenditure, and to the competition of Chinese trade. Results across the two IV strategies are consistent.

Overall, we find that R&D investment growth (60% of which, in our data, consists of employment related costs) has no multiplier effect on local jobs. But, the distinction by routine intensity is crucial, as results differ significantly between HRA and LRA. And, R&D growth changes the composition of employment, although such changes are more pronounced in HRA.

In LRA, R&D growth causes a small loss of workers and population, with on effect

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on the employment shares. The reduction is concentrated in non tradeable services such as construction and retail, accommodation and food, whereas manufacturing employment grows. The reduction occurs mainly among the low educated and self-employed, with an overall increase in the ratio of educated workers in paid employment with respect to low educated in self-employment.

In HRA, R&D growth causes a net increase in employment and in employment shares, mainly in non tradeable services (such as construction and retail, accommodation and food) and in finance and business services, whereas manufacturing employment shrinks. The increase occurs mainly among the low educated and self-employed, with an overall decrease of the ratio of highly educated workers in paid employment. The youngest cohort (16-24) seem to find no employment option in HRA with growing R&D, the middle cohort (25-34) seems to move from paid employment to self employment, whereas the older cohort gain both in terms of paid employment and self-employment.

We investigate the nature of the increase in self-employment as a result of R&D growth in HRA, but we do not find significant differences between part-time and full-time, nor self employed with or without employees. Therefore, we cannot characterise if the self-employment generated by R&D in HRA is due to the opportinities it creates, or to the the jobs it destroys.

Our findings confirm that the short term effect of R&D in local labour markets that are already specialised in routinised jobs might result in a harsher polarisation of the job market. The most difficult challenge for policy makers is to formulate a concerted strategy that aims at steering local labour market upgrading in areas that are characterised by routinised jobs, most likely those that are specialised in mature (manufacturing) industries. Technical change might require high skilled people all along the production cycle: however, creativity and adaptation are qualities and talents that are indispensable too, and that should be harnessed regardless the level of education, and most of all socially protected.

The potential negative effects of R&D investments on the composition of employment in local labour market could represent a particularly challenging conundrum for innovation and industrial policy, within the larger perspective of a UK Industrial Strategy (see the HM Government Green Paper on 'Building our Industrial Strategy'). The trade-off of ensuring continuous support to investments in R&D – most especially in regions that require substantial investments to shift from traditional manufacturing to Industry 4.0, for instance – might need to be counterbalanced by policies of re-training, training and job-protection to tackle the job loss or job-precarisation resulting from innovation. The continuing support to firms investing in R&D should not be questioned, and further coupled with public investments and procurement in basic science. This however should be accompanied by awareness on how to facilitate and promote rejuvenation of mature industries in the areas where a higher shares of routinised workforce is concentrated. While the innovation and industrial policy measures above pertain to the demand side of the skill landscape as a whole, the supply side of skills should be considered a priority. In this respect, the HM Government Green Paper on 'Building our Industrial Strategy' has rightly put forward the need of focusing on Further Education (FE) for the 16-19 cohort. However, the objective of developing skills should not be limited to this. A concerted platform that includes FE,

HE, Continuing Education (CE) and advanced apprenticeships that reduce the burden of access to HE and that upgrade the upper technical skills in disadvantaged regions is to be envisaged. Particularly in the latter areas, Lifelong Learning (LL) and CE should put in place feasible programmes of retraining and re-skilling, possibly in the mature age cohorts.

The present work paves the way to a number of extensions, which mainly entail the analysis of the wage distribution effects of R&D shocks across TTWAs, and a better understanding of the self-employment related to innovative activities. Within the context of boosting UK productivity within a concerted industrial strategy, it is fundamental also to look at which wage deciles and occupational categories, including self-employed across the UK, mostly gain from innovation.

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A   Figures

Figure 1: Business R&D expenditure as share of GDP

Figure 2: Annual TFP Growth
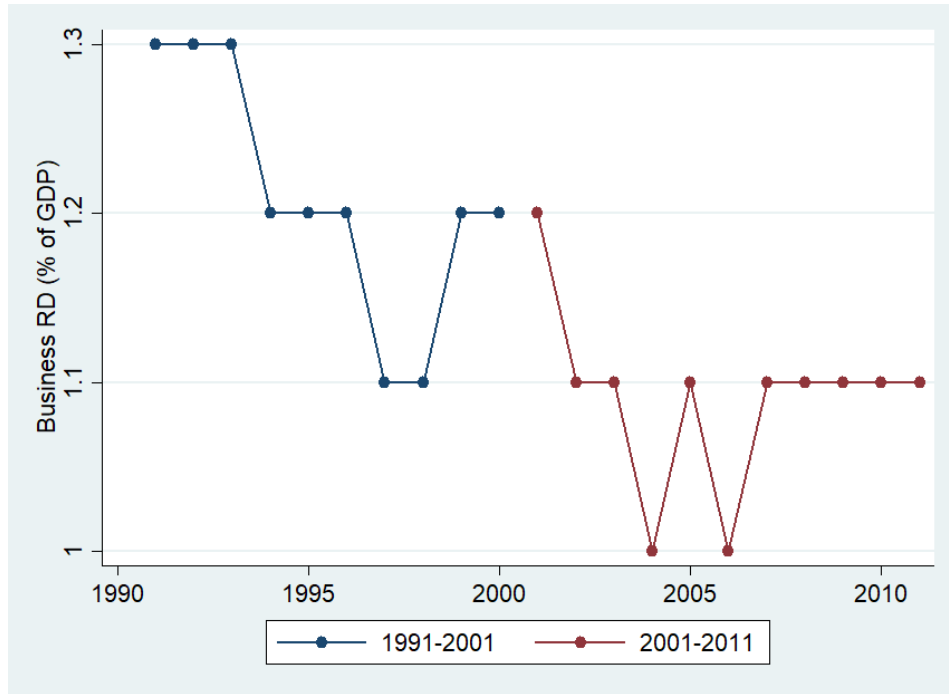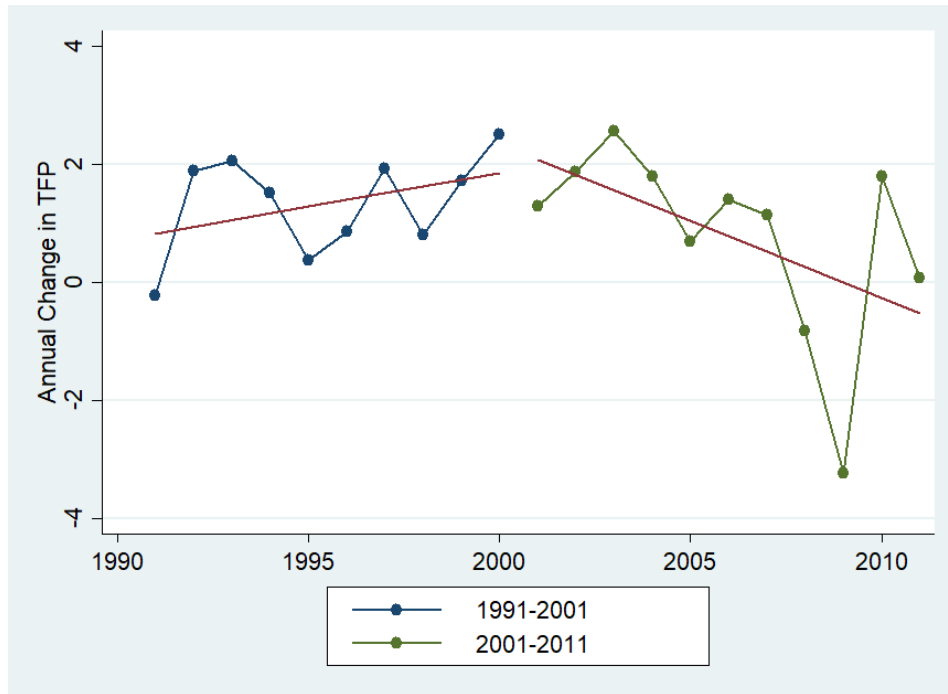
Data source: ONS

Figure 3: Trends of Employment, Unemployment and Self-Employment in the UK, 1991-2013
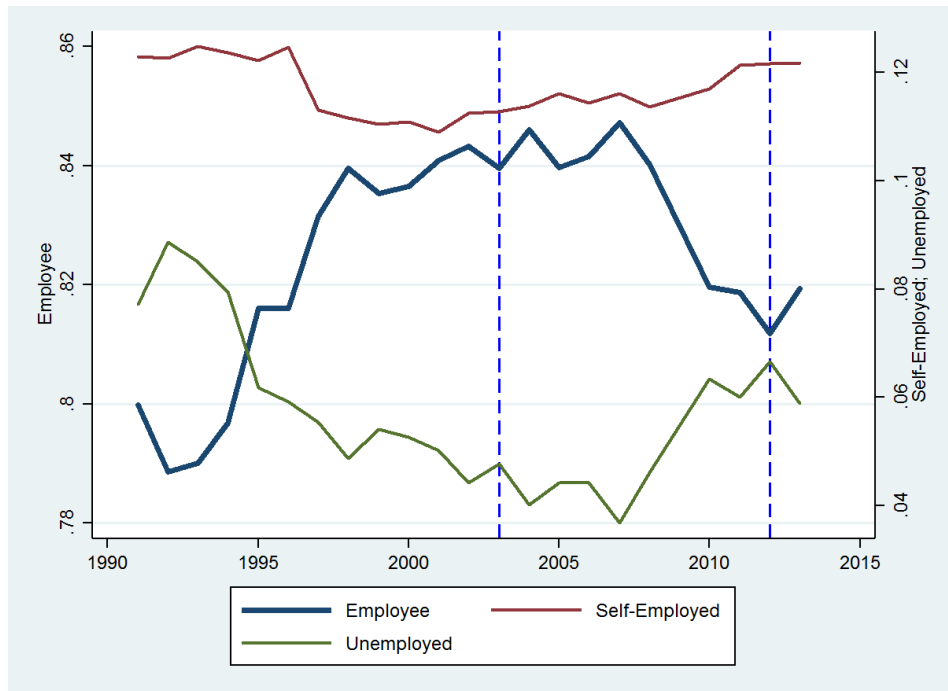
Source: own elaboration based on BHPS

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Figure 4: Self-Employment as % of employed labour force, 1995-2016
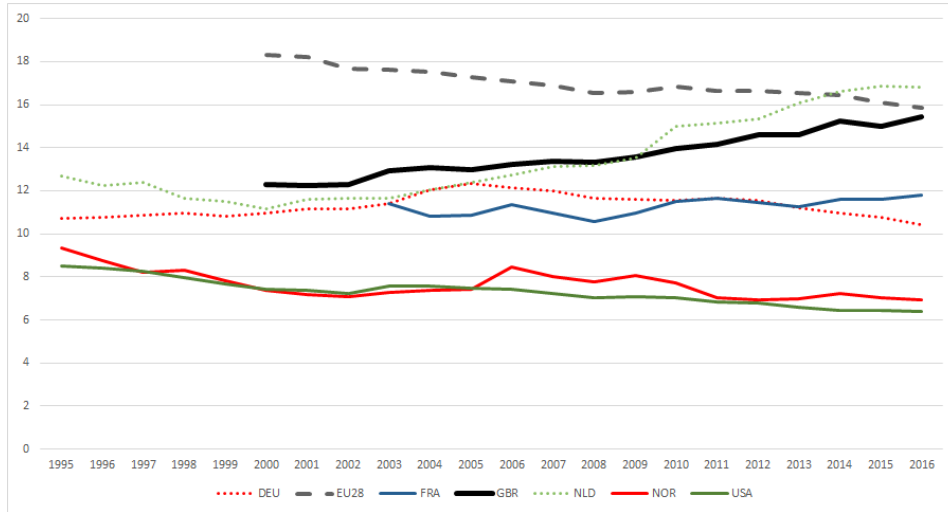
Figure 5: Self-Employment with and without employees, 2001-2016
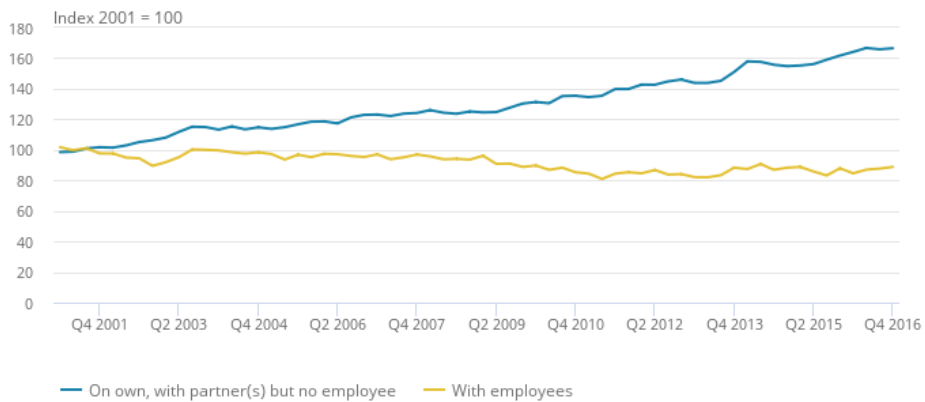
Figure 6: Share of Routine Employment across British TTWAs, 2001

(.16,.25]
(.13,.16]
(.12,.13]
(.1,.12]
[0,.1]
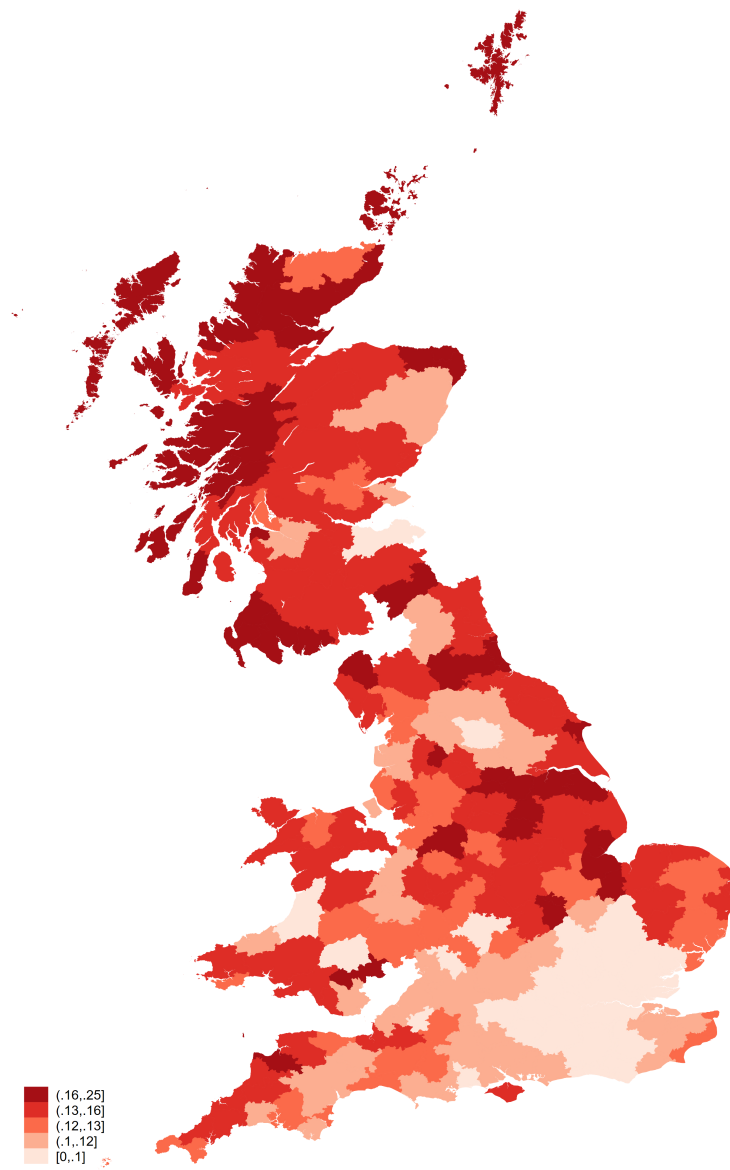
Each TTWA reports the labor share of category NS-Sec 7, *Routine Occupations*.

Figure 7: R&D investments across British TTWAs, 2001

(.63,2]
(.47,.63]
(.34,.47]
[-2,.34]
No data
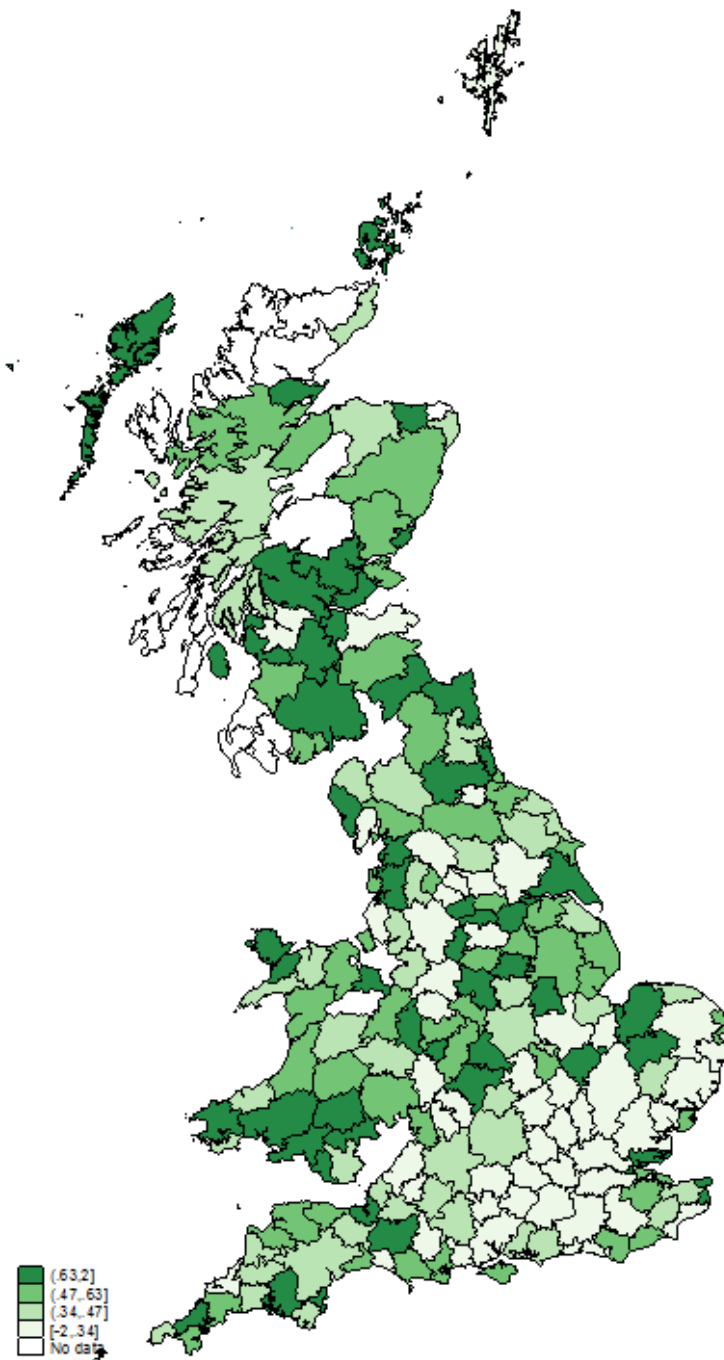
Own elaboration based on BERD

B Tables

Table 1: Share of Routinised Labour: Bottom and Top TTWAs in 2001

TTWA	ϕ
Bottom 5: least routinised	
Reading	.0680643
Guildford and Aldershot	.0691688
London	.0721267
Crawley	.072558
Brighton	.0735549
Average	.1353318
Median	.1335365
Top 5: most routinised	
Fraserburgh	.2338129
Corby	.2335603
Hawick and Kelso	.226953
Girvan	.2176792
Mansfield	.1980037

Notes: [1] ϕ is defined as the share of routine employment over all employment. We use the National Statistics Socio-economic classification (NS-SEC) developed by ONS. ϕ is the share of NS-SEC 7, routine occupations over the rest: NS-SEC 1: Higher managerial, administrative and professional occupations, NS-SEC 2: Lower managerial, administrative and professional occupations, NS-SEC 3: Intermediate occupations, NS-SEC 4: Small employers and own account workers, NS-SEC 5: Lower supervisory and technical occupations, NS-SEC 6: Semi-routine occupations, NS-SEC 7: Routine occupations

Table 2: Employment composition by sector

	2001	2011	Change
Agriculture	0.013	0.007	-0.006
Mining	0.003	0.003	-0.001
Energy	0.008	0.013	0.005
Manufacturing	0.148	0.088	-0.060
Construction	0.068	0.077	0.009
Transport	0.071	0.050	-0.021
Wholesale retail and accommodation	0.215	0.216	0.001
Business and financial services	0.177	0.172	-0.005
Public sector, education and entertainment	0.297	0.375	0.077
Total	**1.000**	**1.000**	

Notes to table 2: [1] Data source: 2001 and 2011 census. [2] We used 2003 SIC codes to map across census waves. Agriculture consists of section A and B, mining is section C, energy is section E, manufacturing is section D, construction is section F, transport is section I, wholesales retail and accommodation group section G and H, business and financial services group sections J and K, while Public sector, education and entertainment groups sections L, M, N and O.

Table 3: First Stage

	Shift-share ΔRD (1)	Trade induced ΔRD (2)
Z	0.82***	79.02***
	(0.07)	(6.16)
F-test	123.80	164.67
Obs.	212	212

Notes to table 3: [1] All dependent variables are log changes in the TTWA from 2001 to 2011 [2] All regressions include country dummies and errors are clustered at country level. [3] Col. 1 reports first stage results using the shift-share Bartik type IV computed as the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D. Col. 2 reports first stage results for the trade induced type IV computed as the predicted change in a TTWA based on the US industries exposition to Chinese imports in 2001. [4] Coefficients that are statistically significant are denoted by the following system: *10%, **5% and ***1%. [5] Calculations include only individuals from 16 to 64.

Table 4: Baseline results

| | Pop. | Employment | | Unemployment | | Ratio |
	Ln(P)	Ln(E)	Ln(E/P)	Ln(U)	Ln(U/P)	Ln(E/U)
	(1)	(2)	(3)	(4)	(5)	(6)
a. Bartik						
ΔRD	-0.09***	-0.08***	0.00	-0.10***	-0.02	0.02
	(0.01)	(0.02)	(0.01)	(0.03)	(0.04)	(0.05)
Obs.	212	212	212	212	212	212
b. Trade Induced						
ΔRD	-0.07***	-0.06***	0.02***	-0.11***	-0.04***	0.04***
	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)
Obs.	212	212	212	212	212	212

Notes to table 4: [1] All dependent variables are log changes in the TTWA from 2001 to 2011; Pop. (col. 1) refers to total population in a TTWA; col. 3 is the ration between col. 2 and col. 1; col. 5 is the ratio between col. 4 and col. 3; and col. 6 is the ratio between col. 2 and col. 4. [2] The independent variable is the log change in R&D expenditure (ΔRD) in the TTWA between 2001-2011. We calculate R&D at the TTWA level as the average R&D expenditure per worker within the TTWA. For each year (2001 and 2011) we use three years of data to improve precision. For year t, we use information of all the firms surveyed by BERD in years $t-1$, t and $t+1$. [3] All regressions include country dummies (England, Scotland and Wales) and errors are clustered at country level. [4] All coefficient are estimated instrumenting R&D expenditure with two instruments: the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D (shift-share Bartik type IV in panel a); the predicted change in a TTWA based on the US industries exposition to Chinese imports in 2001 (trade induced type IV in panel b) [5] Coefficients that are statistically significant are denoted by the following system: *10%, **5% and ***1%. [6] Calculations include only individuals from 16 to 64.

Table 5: Baseline results: heterogeneous effect by initial level of routinisation

| | Pop. | Employment | | Unemployment | | Ratio |
	Ln(P)	Ln(E)	Ln(E/P)	Ln(U)	Ln(U/P)	Ln(E/U)
	(1)	(2)	(3)	(4)	(5)	(6)
a. Bartik						
ΔRD	-0.09***	-0.11***	-0.01	-0.01	0.08	-0.09
	(0.01)	(0.03)	(0.01)	(0.04)	(0.06)	(0.07)
$\Delta RD \times \phi$	0.04**	0.20***	0.15***	-0.71***	-0.76***	0.91***
	(0.02)	(0.08)	(0.06)	(0.21)	(0.23)	(0.28)
b. Trade Induced						
ΔRD	-0.05*	-0.08***	-0.04*	0.23**	0.28***	-0.31***
	(0.02)	(0.01)	(0.02)	(0.12)	(0.10)	(0.12)
$\Delta RD \times \phi$	-0.07	0.08***	0.15***	-1.26***	-1.19***	1.34***
	(0.05)	(0.02)	(0.05)	(0.29)	(0.26)	(0.30)

Notes to table 5: [1] All dependent variables are log changes in the TTWA from 2001 to 2011; Pop. (col. 1) refers to total population in a TTWA; col. 3 is the ration between col. 2 and col. 1; col. 5 is the ratio between col. 4 and col. 3; and col. 6 is the ratio between col. 2 and col. 4. [2] The independent variable is the log change in R&D expenditure (ΔRD) in the TTWA between 2001-2011. We calculate R&D at the TTWA level as the average R&D expenditure per worker within the TTWA. For each year (2001 and 2011) we use three years of data to improve precision. For year t, we use information of all the firms surveyed by BERD in years $t-1$, t and $t+1$. [3] ϕ is a dummy that is equal to 1 when the share of workers in routinised occupations is above the median, indicating a highly routinised are (HRA) [4] All regressions include country dummies (England, Scotland and Wales) and errors are clustered at country level. [5] All coefficient are estimated instrumenting R&D expenditure with two instruments: the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D (shift-share Bartik type IV in panel a); the predicted change in a TTWA based on the US industries exposition to Chinese imports in 2001 (trade induced type IV in panel b) [6] Coefficients that are statistically significant are denoted by the following system: *10%, **5% and ***1%. [7] Calculations include only individuals from 16 to 64.

Table 6: The Effect of R&D on employment, by industry

	Manufacturing	Construction	Transport	Wholesale, retail, accommodation, food	Business and financial services	Public sector, education, arts and entert.
	(1)	(2)	(3)	(4)	(5)	(6)
a. Baseline						
ΔRD	0.29***	-0.12***	0.23***	-0.08***	0.04***	-0.01**
	(0.03)	(0.05)	(0.02)	(0.02)	(0.01)	(0.01)
Obs.	212	212	212	212	212	212
b. By TTWA routinisaiton						
ΔRD	0.35***	-0.18***	0.18***	-0.13***	-0.04	0.00
	(0.01)	(0.05)	(0.01)	(0.02)	(0.02)	(0.01)
$\Delta RD \times \phi$	-0.46***	0.48***	0.40***	0.40***	0.59***	-0.13***
	(0.17)	(0.08)	(0.12)	(0.06)	(0.15)	(0.03)
Obs.	212	212	212	212	212	212

Notes to table 6: [1] All dependent variables are log changes in the TTWA from 2001 to 2011. We estimate the same equation splitting the sample by industry. [2] The independent variable is the log change in R&D expenditure (ΔRD) in the TTWA between 2001-2011. We calculate R&D at the TTWA level as the average R&D expenditure per worker within the TTWA. For each year (2001 and 2011) we use three years of data to improve precision. For year t, we use information of all the firms surveyed by BERD in years $t-1$, t and $t+1$. [3] Panel a reports the baseline results; panel b reports results interacting the change in R&D with the dummy that tkaes the value of 1 when the TTWAs has a share of workers in routinised occupations above the median. [4] All regressions include country dummies (England, Scotland and Wales) and errors are clustered at country level. [5] All coefficient are estimated instrumenting R&D expenditure with the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D (shift-share Bartik type IV). [6] Coefficients that are statistically significant are denoted by the following system: *10%, **5% and ***1%. [7] Calculations include only individuals from 16 to 64.

Table 7: The effect of R&D on employment, by education

	Ln(H)	Ln(L)	Ln(H/L)
	(1)	(2)	(3)
a. Baseline			
ΔRD	0.13***	-0.04	0.16***
	(0.01)	(0.02)	(0.04)
Obs.	212	212	212
b. By TTWA routinisation			
ΔRD	0.12***	-0.07**	0.20***
	(0.01)	(0.03)	(0.04)
$\Delta RD \times \phi$	0.03	0.31***	-0.28***
	(0.05)	(0.08)	(0.08)
Obs.	212	212	212

Notes: [1] All dependent variables are log changes in the TTWA from 2001 to 2011. Column 1 is the number of highly educated individuals. Column 2 is the number of low educated individuals, while column 3 is the ratio between these two numbers [2] High skill = level 4 or more for England and Wales, and levels 3 or above for Scotland. Low skilled = any lower than high skilled [3] The independent variable is the log change in R&D expenditure (ΔRD) in the TTWA between 2001-2011. We calculate R&D at the TTWA level as the average R&D expenditure per worker within the TTWA. For each year (2001 and 2011) we use three years of data to improve precision. For year t, we use information of all the firms surveyed by BERD in years $t-1$, t and $t+1$. [4] Panel a reports the baseline results; panel b reports results interacting the change in R&D with the dummy that tkaes the value of 1 when the TTWAs has a share of workers in routinised occupations above the median. [5] All regressions include country dummies and errors are clustered at country level. [6] All coefficient are estimated instrumenting R&D expenditure with the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D (shift-share Bartik type IV). [7] Coefficients that are statistically significant are denoted by the following system:: *10%, **5% and ***1%. [8] Calculations include only individuals from 16 to 64.

Table 8: The effect of R&D on paid employment and self-employment

	By Emp. Type		Ratio	Ratio in (3) by age group		
	Employee	Self-Emp.	Ratio			
	$Ln(E_E)$	$Ln(E_{SE})$	$Ln(\frac{E_E}{E_{SE}})$	16-24	25-34	35-64
	(1)	(2)	(3)	(4)	(5)	(6)
a. Baseline						
ΔRD	-0.06***	-0.17***	0.11***	0.32***	0.19***	0.07***
	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.00)
b. By TTWA routinisation						
ΔRD	-0.08***	-0.22***	0.14***	0.41***	0.23***	0.08***
	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)
$\Delta RD \times \phi$	0.15*	0.45***	-0.30***	-0.77***	-0.36***	-0.10**
	(0.08)	(0.08)	(0.09)	(0.25)	(0.13)	(0.04)

Notes: [1] All dependent variables are log changes in the TTWA from 2001 to 2011. Column 1 is the number of individuals in paid employment; column 2 is the number of individuals in self-employment; column 3 is the ratio between these two numbers. Column 4-6 report the result for the ratio in column 3 by age cohort: 16-24 (col. 4), 25-24 (col. 5), and 35-65 (col. 6). [2] The independent variable is the log change in R&D expenditure (ΔRD) in the TTWA between 2001-2011. We calculate R&D at the TTWA level as the average R&D expenditure per worker within the TTWA. For each year (2001 and 2011) we use three years of data to improve precision. For year t, we use information of all the firms surveyed by BERD in years $t-1$, t and $t+1$. [3] Panel a reports the baseline results; panel b reports results interacting the change in R&D with the dummy that tkaes the value of 1 when the TTWAs has a share of workers in routinised occupations above the median. [4] All regressions include country dummies and errors are clustered at country level. [5] All coefficient are estimated instrumenting R&D expenditure with the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D (shift-share Bartik type IV). [6] Coefficients that are statistically significant are denoted by the following system:: *10%, **5% and ***1%. [7] Calculations include only individuals from 16 to 64.

Table 9: The effect of R&D on paid and self-employment, by age cohorts

	16-24	25-34	35-64
	(1)	(2)	(3)
a. Employee			
Baseline			
ΔRD	0.03*	-0.21***	-0.03
	(0.02)	(0.03)	(0.02)
By TTWA routinisation			
ΔRD	0.12***	-0.25***	-0.06***
	(0.01)	(0.05)	(0.02)
$\Delta RD \times \phi$	-0.69***	0.32*	0.28***
	(0.17)	(0.20)	(0.03)
Obs.	212	212	212
b. Self-Employed			
Baseline			
ΔRD	-0.29***	-0.39***	-0.10***
	(0.01)	(0.06)	(0.02)
By TTWA routinisation			
ΔRD	-0.30***	-0.48***	-0.14***
	(0.01)	(0.07)	(0.02)
$\Delta RD \times \phi$	0.08	0.68***	0.38***
	(0.11)	(0.22)	(0.04)
Obs.	212	212	212

Notes: [1] All dependent variables are log changes in the TTWA from 2001 to 2011. Column 1 is the number of workers (in paid employment or self-employment within the 16-24 age cohort; column 2 is the number of workers (in paid employment or self-employment within the 25-34 age cohort; column 3 is the number of workers (in paid employment or self-employment within the 35-64 age cohort. Panel a is the number of workers, across cohorts, in paid employment; Panel b is the number of workers, across cohorts, in self-employment. In both panels we report baseline results and results interacting the change in R&D with the dummy that takes the value of 1 when the TTWAs has a share of workers in routinised occupations above the median. [2] The independent variable is the log change in R&D expenditure (ΔRD) in the TTWA between 2001-2011. We calculate R&D at the TTWA level as the average R&D expenditure per worker within the TTWA. For each year (2001 and 2011) we use three years of data to improve precision. For year t, we use information of all the firms surveyed by BERD in years $t-1$, t and $t+1$. [3] All regressions include country dummies and errors are clustered at country level. [4] All coefficient are estimated instrumenting R&D expenditure with the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D (shift-share Bartik type IV). [5] Coefficients that are statistically significant are denoted by the following system:: *10%, **5% and ***1%. [6] Calculations include only individuals from 16 to 64.

Table 10: Self-Employment by type of self-employment

	Total	SE with employees			SE without employees		
		Total	Part-time	Full-time	Total	Part-time	Full-time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a. Baseline							
ΔRD	-0.14***	-0.18***	-0.22***	-0.17***	-0.09***	-0.06**	-0.09***
	(0.03)	(0.04)	(0.05)	(0.03)	(0.02)	(0.02)	(0.02)
Obs.	212	212	211	212	212	212	212
b. Interaction: slope							
ΔRD	-0.19***	-0.23***	-0.31***	-0.21***	-0.15***	-0.12***	-0.16***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)
$\Delta RD \times \phi$	0.40***	0.41***	0.72***	0.35***	0.52***	0.46***	0.55***
	(0.06)	(0.10)	(0.13)	(0.10)	(0.06)	(0.11)	(0.07)
Obs.	212	212	211	212	212	212	212

Notes to table 10: [1] All dependent variables are log changes in the TTWA from 2001 to 2011 in the number of self-employed individuals in total (col. 1) and grouped in 4 categories: with employees (col. 2) (part (col. 3) and full time (col. 4)) and without employees (col. 5) (part (col. 6) and full time (col. 7)). [2] The independent variable is the log change in R&D expenditure (ΔRD) in the TTWA between 2001-2011. We calculate R&D at the TTWA level as the average R&D expenditure per worker within the TTWA. For each year (2001 and 2011) we use three years of data to improve precision. For year t, we use information of all the firms surveyed by BERD in years $t-1$, t and $t+1$. [3] All regressions include country dummies and errors are clustered at country level. [4] Panel a reports the baseline results; panel b reports results interacting the change in R&D with the dummy that tkaes the value of 1 when the TTWAs has a share of workers in routinised occupations above the median. [5] All coefficient are estimated instrumenting R&D expenditure with the predicted change in a TTWA based on the initial industry composition and the national aggregate change in R&D (shift-share Bartik type IV). [6] Coefficients that are statistically significant are denoted by the following system: *10%, **5% and ***1%. [7] Calculations include only individuals from 16 to 64.