R&D and Employment Composition: Evidence from UK Local Labour Markets*

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Abstract

This paper provides a comprehensive account of the local employment impact of firms' investment in R&D in UK local labour markets. We focus on the composition effects across industries and employment types. We distinguish the impact of R&D across areas with different initial shares of workers in routinised occupations and industry shares. Drawing on two instrumenting strategies, our results consistently suggest that R&D change, on average, exerts a small negative effect on local employment, mainly through changes in its composition. Results differ significantly for local labour markets with different initial shares of workers in routinised occupations. Areas with below median shares of workers in routinised occupations experience a relative reduction in low educated employment in non tradeable services and self-employment. In areas with above median shares of workers in routinised occupations, low education employment also increase, in tandem with an increase in non tradeable services; all the positive employment change occurs in self-employment. We qualify the positive effect of R&D on self-employment in highly routinised areas and find no evidence to distinguish if it is driven by opportunities related to R&D investment or necessity.

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

JEL: O33; J24

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1 Introduction

The effect of technical change on the rate, growth, and composition of employment has long been debated, since Ricardo to the more recent routine replacing technical change theory (Freeman and Soete; 1987; Freeman et al.; 1982; 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).

At the firm level, there is substantial evidence that innovative firms hire more workers. Product innovation generally is found to have a stronger impact than process innovation, particularly in large and high tech firms, independently from the measure of innovation used.[2]

These studies have two main limitations. First, innovation is usually measured with innovation surveys or patents. In surveys, firms self-assess their innovativeness. Patents measures firm innovativeness, but not the investment in innovative activities, which is only partially correlated with R&D.[3] Firms' choice to invest in R&D is strategic: 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 and technologies, or generate them. At the firm level, R&D demands employment in occupations requiring abstract skills (e.g. engineers). R&D may lead to increased productivity and new products, which may result in an increased demand, and employment, in all occupations (Bogliacino et al.; 2012).

Second, firm level studies do not account for the impact of innovative firms on the local or national labour markets. The effect of firm innovative activities on workers at the market level may differ from the within firm impact, for example because of agglomeration economies, increased competition, or market stealing. In the local labour market, an increase in skilled R&D jobs may have a multiplier effect (Moretti; 2010), by attracting new skilled workers, entrepreneurs and innovators (Aghion et al.; 2019).[4]

The contribution of this paper is to empirically estimate the local employment impact of R&D in manufacturing on employment. We use data on UK local labour markets.

We decompose the overall impact on local labour markets between level and composition effects. We focus on the composition and show that the overall negative impact of R&D on employment is due to the fact that R&D reduces the overall negative employment trend in manufacturing and transport sectors, and in paid employment. But R&D reduces

[1]See, among others, Acemoglu and Restrepo (2019a,c,b); Bessen et al. (2019); Graetz and Michaels (2018); Arntz et al. (2017); Nedelkoska and Quintini (2018).

[2]See for example Harrison et al. (2014) for evidence based on the introduction of process and product innovations across several EU countries countries; see Calvino and Virgillito (2018) for a recent survey.

[3]Two exceptions are: Bogliacino et al. (2012), who studies the relation between large firms R&D and firm employment across several countries; and Coad and Rao (2011), who studies the same relation for US firms comparing R&D and patenting activity. Both studies find a positive relation between innovation and employment a the firm level, but fail to identify the causal impact of R&D.

[4]Hornbeck and Moretti (2018) focus on productivity gains and find that, on average, they increase employment and workers's earnings in US local labour markets. With respect to the adoption of new capital goods, Autor and Dorn (2013) have documented an increase in employment following adoption of ICT in US local labour markets, whereas industrial robots seem to have a negative impact on both employment and earnings (Acemoglu and Restrepo; 2019b). Focusing on product innovation (patents), Gagliardi (2014) documents a negative impact on employment in UK local labour markets, worsened in labour markets specialised in mature industries.

employment in sectors that experience and overall increase in jobs, such as construction and the public sector and in self-employment, which also grows.

We also account for two aspects of the initial composition of local labour markets that may condition the local employment impact of R&D on employment, and which have been considered separately in the literature: sector composition (Gagliardi; 2014; Acemoglu and Restrepo; 2019a)[5] and skill composition (Autor and Dorn; 2013).[6]

Our research design most closely follows studies on the impact of TFP growth (Hornbeck and Moretti; 2018), and the adoption of new technologies (Autor and Dorn; 2013) on local labour markets (in the US).

We use confidential firm level data on 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 – accounting for 80% of UK R&D investment. 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 industry, age, education, and type of employment, representative at the TTWA level. We distinguish between TTWA that have a share of workers in routinised occupations above the median (high routinised areas, HRA), from TTWA whose share is below the median (low routinsed areas, LRA).

We focus on the 2001-2011 decade, during which employment has decreased, although relatively less than paid employment, due to a contemporaneous steady growth of self-employment (Fig. 1).

[Figure 1 around here]

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 exogenous R&D change in a local labour market, we use two instrumental variables that exploit the past local industrial specialisation, in relation to their propensity to invest in R&D 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, we instrument R&D with the predicted change in a TTWA based on the US industries exposure to Chinese imports in 2001 (Bloom et al.; 2016). Even if the two instruments rely on different assumptions and sources of variation, results are remarkably consistent across the two instrumentation strategies.

We find that the total local employment impact of R&D investment on employment is negative. This is explained mainly by the reallocation components that sum up to the total impact. R&D has a positive impact on paid-employment in industries whose share

[5] By employing a shift share instrument that weights the national increase in R&D expenditure with local shares of employment across industries

[6] By distinguishing areas with high and low shares of workers employed in routine occupations. See below for the estimation strategy and the definition of routinised occupations.

decrease nationally (manufacturing, transport and business services), and a negative impact on self-employment and in industries whose share grows nationally (construction, trade accommodation and good, and public sector. education and entertainment). Private R&D investments seem to counter the general employment trends in local labour markets. But this counter-trend effect in manufacturing and paid-employment is not sufficient to balance the overall negative impact on self-employment and in services.

This overall impact reflects employment outcomes in areas initially populated by a below-median share of routinised workers. In areas with initially above-median shares of routinised workers (HRA) private R&D investment has an almost inverse impact: employment increases. This is explained by a reallocation effect inverse to that of of LRA: a positive change in R&D investment reduces substantially employment in manufacturing and increases employment in all non tradeable sectors (whose share grows nationally) and in self-employment.

The quality of employment seems to increase in LRA: paid and highly educated employment increases with respect to self-employment and low educated. The net loss of employment in LRA is concentrated among low educated self-employed in service industries. The evidence fits well with the skill biased technological change theory (Acemoglu and Autor; 2011; Saint-Paul; 2008), but not necessarily with theories that would predict positive local externalities of R&D (Feldman and Kogler; 2010; Glaeser and Maré; 2001).

Instead, in HRA private R&D investment increases employment also among low educated workers, in self-employment. Taken together, the evidence in HRA seems to support the extreme skill complementarity hypothesis (Eeckhout et al.; 2014): the positive change in occupations related to R&D investment is accompanied by a positive change in low educated jobs, in non-tradeable industries (e.g. personal services and construction), and/or in self-employment.

We qualify the type of self-employment being created as a result of an increase in R&D in HRA, distinguishing between part- and full-time and with and without employees. Theory would suggest that R&D spillovers may crate opportunities for new innovative ventures We do not find significant differences among the different types of self-employment created by R&D. Based on earlier finding that the increase in self-employment in the UK is correlated with firm innovation only in urban areas, whereas in rural areas it is more related to the lack of employment opportunities (Faggio and Silva; 2014), we may speculate that our results suggest a raise in refugee self-employment in service sectors (e.g. personal service occupations), rather than self-employed driven by technological opportunities. More research, with better data, is needed to study the nature of self-employment in relation to innovation.

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 relevant literature and discusses the rationale of 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 The Local Employment Impact of R&D

Our empirical investigation is motivated by a simple conceptual framework. An investment in R&D may have several direct and indirect impacts on a local labour market. These impacts may vary across sectors of the local labour market and by occupation. The overall local employment impact of R&D then depends on how it distributes across sectors, on the initial sector composition, and on the occupational composition.

Concerning direct and indirect impacts, R&D captures innovation effort and thus the resources that the firm commits to innovation, including labour.[7] In the case of the UK, between 2001-2011, labour account for 60% of private R&D expenditure. R&D may also lead to the creation and adoption of new technologies in production processes,[8] and of marketable novel applications, which may increase firms' market shares and knowledge stock (Freeman and Soete; 1987; Freeman et al.; 1982).[9] Theory from economic geography also predicts that innovative areas may bring a wage and employment premium, attracting jobs, investment and firms (Glaeser and Maré; 2001; Meliciani and Savona; 2014; Mion and Naticchioni; 2009; Hornbeck and Moretti; 2018). Innovative firms may also drive competing firms out of the market, with an overall negative effect on employment Gagliardi (2014).

Concerning how these impact may vary across sectors of a local labour market, as firm R&D distributes gains and losses among industries, labour will also tend to reallocate proportionally. For instance, Autor and Salomons (2018) show that reduction in within manufacturing employment related to an increase in TFP, in 19 OECD countries over more than 35 years, was overcompensated by an increase in employment in other industries, such as services. Although labour reallocation occurs also across labour markets, Acemoglu et al. (2016) discuss that this migration effect is modest with respect to reallocation between industries within labour markets. R&D may also create alternative earning prospects in the form of self-employment, which differ with respect to the impact on the paid employees.[10] We distinguish two main mechanisms that are often discussed in the literature. On the one hand, R&D may create spillovers (Feldman and Kogler; 2010), in the form of opportunities that may be captured by new businesses. On the other hand, labour replacing innovations, competition, and skills obsolescence due to R&D may make some jobs obsolete, pushing workers to self-employment due to necessity (Bünstorf; 2009). In both cases, R&D may create the conditions for workers to be better-off in self-employment than in paid employment (Blanchflower and Oswald; 1998): either to exploit the opportunities (Bloom et al.; 2013), or to cope with the unemployment (Thurik et al.; 2008), that may be generated by

[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] Increased productivity may reduce prices of the final goods, thus increasing demand; extra profits may be invested, generating new jobs; and increased wages linked to productivity growth may attract new workers (Pessoa and Reenen; 2013).

[9] Product innovation might create new jobs through diversification and increased variety, provided that new products do not completely displace obsolete products.

[10] Self-employment has increased substantially in the UK since 2000 (Fig. 1 and Haldane (2017)), and alternative work arrangements represent the bulk of the US employment growth over the last few years (Katz and Krueger; 2016).

R&D investments.

Concerning the initial composition, the overall impact will result from the sum of the positive and negative impacts of R&D across sectors. For instance, (Gagliardi; 2014) shows that the impact of firm patenting on employment across UK local labour markets depends on the initial local industrial structure: local labour markets with more mature industries experience a negative impact on employment. We are not aware of evidence that distinguish the impact of innovation distinguishing by paid employment and self-employment.

The overall impact of R&D also depends on the initial skill composition across industries (Autor and Dorn; 2013). R&D investments in areas with high educated and skilled workforce in non-routine occupations may attract more high educated skilled workers to work in the R&D activities, and in related spin-offs. If the R&D growth occurs in areas with high shares of routinised occupations, it may not generate demand for local employment which do not have the skills to work in the new jobs commanded by R&D investments. However, direct firm level and regional level effects may also create employment for routine occupations, e.g. via an increase in sales of the innovative firms. Moreover, 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). The routine-replacing technical change (RRTC) framework (Autor and Dorn; 2013; Goos et al.; 2014; Van Reenen; 2011) attributes the main cause of job market polarisation to the initial task specialisation of labour markets. Eeckhout et al. (2014) also show that larger cities are subject to extreme skill complementarity: high-skilled workers benefit from the presence of low skilled workers offering personal non-tradeable services.

Finally, the initial occupational and industrial structure is also likely to influence the impact of R&D on the composition of activities among the self-employed. For high levels of skill mismatch between local workers and the jobs created by R&D, workers with redundant skills are likely to seek alternative forms of employment as a coping strategy (Åstebro et al.; 2011; Vona and Consoli; 2015). Following the extreme skill complementarity hypothesis, these workers might have a better chance to offer personalised services to those who are employed in R&D related activities (Autor and Dorn; 2013). For instance, Levine and Rubinstein (2017) document that while incorporated self-employment is usually associated to increases in non-routinised workforce, unincorporated self-employed make use of relatively higher routinised workforce. R&D may provide opportunities for entrepreneurs or push workers towards self-employment as a coping strategy (Levine and Rubinstein; 2017). The larger the initial share of routinised workers, the higher the likelihood that they will use self-employment as a coping strategy, rather than seeking new opportunities generated by R&D spillovers.

Our empirical analysis is structured as follows. We first estimate the impact of R&D activities of all firms in a local labour market on the total level of employment. Second, we estimate the total impact of R&D on the composition of local employment across industries and employment type to study the composition effect. We distinguish between manufacturing, construction, transport, wholesale and retail trade, accommodation and food, business and financial services and public sector, education, arts and entertainment (Tab 8). We next distinguish between employment and self-employment. To study which self-employment may be created by R&D, we distinguish between three age cohorts and between six types of self-employed, combining with and without employees, and part- and full-time. 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 (Haldane; 2017).[11] 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).

Third, to estimate the effect of the initial occupational structure, we run all the analysis distinguishing between local labour markets with high and low ratios of jobs in routine intensive activities in the initial period, before the measured investment in R&D.

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. TTWA are spatial units created to approximate labour market areas, where at least 75% of the workers live in the same area, and 75% of the workforce that live in the area works in the same area.

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[12] and NOMIS[13].

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 labour accrued by *routine occupations* in every TTWA in 2001. Figure 2 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.[14]

[11]See Fig. 2 in the 2018 ONS report on "Trends in self-employment in the UK" (last accessed on 15 October 2019.)

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

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

[14]Table 7 in the Appendix 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. we define ϕ 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. The NS-SEC classification, develops upon a sociological classification known as the Goldthorpe schema (Goldthorpe; 1997) and differentiates occupations on the basis of employment relations and conditions. A major distinction is between occupations that are regulated by a service relationship and those that are regulated by a labour contract, although intermediate forms between the two extremes exist. In the former, the employee provides a service to the employer in return for a compensation, in the form of immediate reward (e.g. salary) and long-term benefits (e.g. assurance of security, career opportunities). In the latter, the employee supplies a discrete amount of labour and

[Figure 2 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 where only 9.6% of the businesses with less than 10 employees are sampled (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 investors, without making claims about statistical representation for the R&D expenditure of all firms in the UK.

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 Business Structure Database (BSD),[15] 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 change at the TTWA level: $\Delta RD_i = \hat{\theta}_{2011} - \hat{\theta}_{2001}$.

4 Econometric strategy

Our main objective is to estimate the local employment impact of changes in R&D investment. Operationally, we employ a set of dependent variables that capture different impacts on the level and composition of the local labour market outcomes. These include: employment, 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 change and local labour market outcomes is then defined by the following equation:

receives a wage based on the amount of work done (or time worked). The NS-SEC classification considers also the employment relation. This refers to the location of the occupation in the system of authority and the degree of control and autonomy. Combining aspects related to labour regulation and conditions, the NS-SEc classification defines routine occupations as occupations that are regulated by a basic labour contract and have the least need for employee discretion. The NS-SEC classification identifies routine occupations related to: sales and service, production, technical, operative and agricultural (ONS; 2005). In addition to routine occupations (NS-SEC 7) the other occupation categories are the following. 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. ϕ is the share of NS-SEC 7, routine occupations over the rest.

[15] The BSD covers almost all business organisations in the UK.

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

We take first differences of all variables, ruling out any unobserved fixed effect at the TTWA level.[16] 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. (2003) 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 i^{th} TTWA is characterised by an above-median share of workers employed in routine occupations in 2001.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 investments may generate spillovers, which may attract skilled labour (e.g. engineers). The increase in the supply of engineers, in turn, may provide an incentive for firms in the same area to increase investment in innovation activities. As a result, employment outcomes may influence R&D activities in a TTWA. Second, there may be time varying unboserved factors not captured in our estimation that may affect changes in both employment and R&D 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 Variable (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 Bartik shift-share 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.

[16]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.

4.1 Shift-share instrument

Here we detail our first instrumenting approach. We use the initial employment share of industries in TTWA i to predict i's change in R&D, multiplying the national R&D change (excluding TTWA i) by i's industry shares.[17] 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 the different industry compositions across TTWA in the initial year (2001). As argued by Baum-Snow and Ferreira (2015), "[t]he validity of this instruments relies on the 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 nationwide 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.[18]

We proceed in two steps. First we estimate the aggregate change 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.[19] 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 employment 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

[17] We re-run our estimates using the initial output share of industries using turnover and results are strongly consistent with our main results (reported in Appendix C.1).

[18] 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).

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

R&D expenditure in industry j at national level, excluding TTWA i.[20] We then define the instrument for TTWA i R&D change as the weighted sum of industry's j R&D where the weights are the TTWA industry shares (computed with employment):

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

Figure 3 maps the variation of R&D investment change between 2001-2011 across TTWAs (as resulting from our IV strategy).

[Figure 3 around here]

4.2 Trade induced technical change instrument

Here we detail our second instrumenting approach. This strategy exploits the sudden increase in Chinese imports in the UK 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 from Chinese trade 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 first build a measure of UK industries' exposure to Chinese trade. Because UK imports from China and employment may be correlated with unobserved industry shocks in the UK, we use US industry exposure instead Autor et al. (2013, 2015).[21]

We multiply the change in US imports from China in industry j between 2001 and 2011 by the initial share of UK imports from China in industry j, weighted by the employment share of industry j 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 in TTWA i; η_{ij} is the 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 used employment data from the Business Structure Database (BSD), which covers the universe of UK firms.

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

[20] 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, $\Delta RD_{-ij} = \hat{\theta}_{-ij,2011} - \hat{\theta}_{-ij,2001}$

[21] Griffith et al. (2006) show that an increase in US R&D activity is positively associated to increases in the productivity of UK firms, and the magnitude is similar to that associated to an increase in within firm R&D.

5 Results

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

Table 2 reports the baseline estimates of the average impact of R&D investment change on employment (col. 1) and employment-to-population ratio (col. 2) across UK TTWAs over the period 2001-2011.[22] Panel (a) reports results using the Bartik shift-share instrument, and panel (b) reports results using the trade induced instrument. In general, results are consistent to the choice of IV. Both instruments yield qualitatively similar results: a small reduction in employment, but not in employment-to-population ratio. The magnitude of the economic impact is similar across both instruments.

In particular, we find that a 10% increase in R&D per employee, for the average TTWA, leads to 0.6-0.7% reduction in employment (col. 1, panels a and b).

[Table 2 around here]

This result differs from earlier results that use different measures of local innovation. The research that uses job growth in high tech sectors find a positive effect on employment. The research that uses patents to measure innovation finds a negative association to employment rates. We seem to find that R&D lays in between these two results. This may be due to the three effects coming from within the firm, which are stronger when measuring R&D than when measuring patents. First, 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). Second, there is no linear relation between R&D investment and patenting. While patenting firms are likely to perform R&D at some stage, not all firms investing in R&D do patent. And for the same level of R&D, patenting output differ substantially across industries due to differences 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). The use of patents as a proxy for technical change in this context might risk to underestimate the employment in R&D and complementary activities effect and the agglomeration economies effect. Third, 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).

How does the effect of R&D on employment differ when interacted with 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.[23] HRA have a share of routinsed workers above the median (0.13, see Table 7); LRA below the median.

[22] Table 1 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).

[23] 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.

Table 2, col. 2 (panels a & b), shows that the effect of R&D on employment differs across HRA ($\phi = 1$) and LRA. In HRA, a 10% increase in R&D investment may lead to an increase in employment between 0-0.6%.

These estimates (robust to both identification strategies) suggest the counter-intuitive result that, for the average worker, all the positive impact (of R&D expenditure) on the level of local employment in the UK comes from HRA.

To explore this result further, we study which employment is generated/destroyed by R&D investment in terms of workers' education. As suggested by the extreme skills complementarity hypothesis, it is possible that R&D investment generates employment in firms investing in R&D and related activities, as well as low skill jobs in personal services.

As noted above, results across both identification strategies are remarkably consistent. Because this is the case for all estimations discussed below, to facilitate readability we discuss results using the Bartik shift-share IV only. Results are extremely similar when we use the trade induced IV and are reported in Appendix C.

Table **??** reports the estimates of the total local employment impact of R&D investments on high and low educated workers (Panel a) and the effect distinguishing by degree of routinisation of the TTWA (Panel b).[24]

[Table 3 around here]

Overall, we find that a positive change in R&D increases the number of highly educated workers, overall and relative to low educated workers. This is well explained by the skill biased technical change theory (Acemoglu and Autor; 2011; Saint-Paul; 2008). Conditioning to the initial routinisation, we find that in HRA R&D induces an increase in the number of both low and high educated workers (although the high educated prevail).[25] This is counterintuitive, but is line with the mechanisms discussed in the routine-replacing technical change theory (Autor and Dorn; 2013; Goos et al.; 2014; Van Reenen; 2011), and with the extreme skills complementarity hypothesis (Eeckhout et al.; 2014).

In sum, the total impact of R&D investment on the level of local employment is to: reduce employment in LRA, replacing high educated workers for low educated workers; increase employment in HRA, both high educated workers (possibly in R&D related jobs) and low educated workers (possibly in complementary low skilled jobs).

R&D in LRA seem to create less low skilled jobs than it does in HRA; in fact low skilled jobs reduce in LRA (.5% for a 10% increase in TTWA R&D investment).

To further explain the impact of R&D investment on the level of local employment, we investigate heterogeneous effects across industries and types of employment (paid employment and self-employment). As suggested by the extreme skills complementarity hypothesis, and results on the education of the employment created, it is possible that a pool

[24] 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.

[25] We note that estimates using turnover to compute the industry share by TTWA with the shift-share instrument (Tab. 10), and with the trade induce instrument (Tab. 13) suggest that in HRA the ratio of high to low educated workers actually reduces.

of routinised workers in HRA provides the condition for the reallocation of jobs to services related to R&D investment.

5.2 The Heterogeneous Effect of R&D Investment across Industries

To investigate what kind of employment is created (lost) by R&D in routinised (non-routinised) local labour markets, we re-estimate Equation 3 by sector of activity (industry). Table 4 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 4 around here]

We find that R&D investment has an overall positive effect on local employment in manufacturing (col. 1), transport (col. 3) and business and financial services (col. 5) and shrinks in construction (col. 2) and non tradeable services such as trade, accommodation and food (col. 4) and the public sector (col. 6).[26].

Conditioning the results to the initial level of routinisation (panel b), we find that the overall impact across industries is dominated by what happens in LRA, and helps explain the overall negative impact of R&D on employment in LRA. Following an increase in R&D investment, employment grows in industries that experience a decline in employment shares at national level (Tab. 8 in the Appendix), and shrinks in industries that experience an increase in employment shares at national level.

The effect of R&D change on employment in HRA is almost symmetric with respect to the overall effect dominated by LRA. First, there is a substantial reduction in manufacturing jobs (col. 1): a 10% increase in R&D reduces manufacturing jobs in HRA by 4.5%. This is offset by job creation in construction and all service industries. A 10% increases in R&D over 2001-2011 increases employment in construction by 4.4% (col. 2), trade, accommodation and food services by 1.7%, business and financial services by 4.2%[27] and in the public sector by 2%.

Results suggest a quite significant impact of R&D investment on the local change in composition of employment across industries. An increase in R&D investment triggers de-industrialisation (or tertiarisation) in areas which were dense in highly routinised jobs. Results are again in line with the evidence on polarisation and extreme skills complementarity (Autor and Dorn; 2013; Eeckhout et al.; 2014; Mazzolari and Ragusa; 2013): as more workers are employed in R&D activities, we observe substantial increase of employment in low skilled non tradable services, such as construction, trade accommodation and food, which include a large component of the personal services. Instead, in local labour markets where a small share of jobs where in routine occupation, new investment in R&D reduce employment in non tradeable services and increase employment in manufacturing.

[26]Labour composition across industries is reported in table 8 in the Appendix

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

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

R&D investments may generate opportunities for new ventures related to the innovation activities, and/or to respond to the demand for new (low skilled) personal services. In this section we estimate the heterogeneous impact of R&D investment on paid employment and self-employment.[28]

Table 5 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 5 around here]

We find that, on average, a 10% increase in R&D reduces both paid employment (by 0.5%) and self-employment (by 1.6%) (Cols. 1 & 2), but the effect is stronger on self-employment, resulting in an increase in the ratio between paid employment and self-employment of 1.1% (Col. 3). Results add one more piece to the puzzle explaining the overall negative local employment impact of R&D: this is driven by self-employed, which do not seem to be attracted to areas where R&D increases, on average. This seems to suggest that, across the UK, R&D does not create opportunities for self-employed. This may be because UK TTWA are specialised in industries that appropriate innovations (low spillovers), and offer few opportunities for new entrants (high barriers).

When we condition to the initial share of routinised workers, we find that the results just discussed reflect the impact of R&D in LRA. The effect is significantly different in HRA, where a 10% change in R&D investment reduces the number of workers in paid employment by .5% (col. 1), but increases the number of self-employed by 4.5% (col. 2), resulting in a 4.4% increase in the ratio between self-employment and paid employment (Col. 3). This composition effect contributes to explain the overall positive employment impact of R&D in HRA, togehher with the industry composition.

The increase in the ratio of self-employed to paid employment may be because in HRA R&D activities creates more entrepreneurial opportunities than in LRA, or because R&D investment creates skills mismatches, leading individuals to resort to self-employment as an alternative to unemployment. Our data do not allow us to desegregate by industry and type of employment, so we cannot estimate if the self-employed grow more in the non-tradeable industries or in manufacturing (which, overall, declines). We make a first attempt to distinguish between more opportunity and necessity driven self-employment below.

Table 5 also distinguishes the impact of R&D investment on the local ratio between paid employees and self-employed by age cohorts. Particularly relevant is the impact in HRA,

[28] The information on self-employment is self-reported by the household. The survey distinguished between: working as an employee; government sponsored training scheme; self-employed or freelance; or working paid or unpaid for your own or your family's business; away from work ill, on maternity leave on holiday or temporarily laid off; and doing any other kind of paid work. We regard to self-employed as to those who answer "self-employed or freelance".

where a 10% change in R&D investment induces an increase in the share of self-employed over paid employment of 8.4% among the youngest (16-24, col 4), 6.2% among the middle cohort (25-34, col 5) and 2.2% among the oldest cohort (35-64, col 6).

Qualifying the Effect on Self-Employment

From the above results, the increase of self-employed in the local labour market is an important component of the total local employment impact of R&D in HRA. The increase in self-employment can be the result of new opportunities created by the local R&D investment (Bloom et al.; 2013), reduced jobs in routinised occupations (Autor and Dorn; 2013), increased demand in personal services Autor and Dorn (2013); Mazzolari and Ragusa (2013), or a combination of those. To discriminate between the three potential mechanisms, we investigate the type of self-employment activities that are created in different local labour markets, distinguishing between self-employment with and without employees and part/full time. First, self-employed who hire one or more workers tend to be entrepreneurs seeking for opportunities rather than for necessity (Coad et al.; 2017). Second, it is probably safe to expect that entrepreneurs that invest in activities related to R&D will tend to work full time in their firm.

Table 6 reports the estimates of the overall effect of R&D investments on part-time (cols. 2,5) and full-time (cols. 3,6) and self-employment with (cols. 1-3) and without employees (cols. 4-6). We condition also for the degree of routinisation of the TTWA (Panel b).

[Table 6 around here]

Results confirm that, on average, an increase in R&D investment reduces the number of self-employed individuals, driven by the impact in LRA. Self-employed in HRA, instead, increase as an outcome of R&D investment. However, we do not find significant differences among different types of self-employed, especially with and without employees. A 10% increase in R&D in HRA increases self-employed with employees by 1.8% and self-employed without employees by 3.7% but the difference is not statistically significant. Similarly, among the self-employed 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 in HRA 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 because of skill mismatches generated by the R&D investment.

6 Conclusions

The extant literature has shown that innovation leads to net employment growth within innovating firms. The impact of innovation outside the firm, in labour markets, has been studied in relation to increased jobs in high tech sectors, adoption of ICT and automation, and increase in TFP. The evidence here is more mixed: jobs in high tech sectors and TFP seem to have a positive impact, but for automation and innovation output measured with patents, the impact can be negative – for example for robots (Acemoglu and Restrepo; 2019b).

Crucially, the impact of innovation on the local labour market depends on their initial composition in terms of sectors and occupations. The initial composition is particularly important to understand the contribution of the local composition of employment on the overall local employment impact of innovation. The literature has documented the role of technology adoption in changing the skill composition of employment, resulting in labour market polarisation (Autor and Dorn; 2013) and extreme skill complementarity (Eeckhout et al.; 2014; Mazzolari and Ragusa; 2013).

This paper adds to this evidence in several ways. First, we measure innovation in a comprehensive way, capturing firm intention to innovate: investment in R&D. We discuss the advantages, and limits, of referring to a measure that captures a 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, providing a better understanding of the composition effect on the local employment impact of R&D. Fourth, we extend the analysis on the composition to include self-employment, and we make a first attempt to study whether the self-employment generated by innovation in highly routinised areas is due to the opportunities that emerge from R&D spillovers, the potential increase in the demand for personal services, or by the need to cope with skills mismatches.

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

Overall, we find that an increase in R&D investment (60% of which, in our data, consists of employment related costs) has a negative impact on local jobs. This negative impact is explained by the heterogeneous effect that R&D investment has across industries, altering the composition of workers. The distinction of local labour markets by their initial occupational composition in terms of routine intensity is crucial. Results between HRA and LRA are almost reversed – although LRA dominate in the UK average effect.

In LRA, increased R&D causes a loss of workers. The reduction is concentrated in construction and non tradeable services such as trade, accommodation and food and the public sector. This is only partially compensated by an increase in manufacturing employment. Because the employment share of services increases in the same period, at the expenses of manufacturing, the local reallocation effect contributes negatively to local employment impact of R&D. As predicted by theory, the negative impact of R&D on local employment concerns mainly the low educated and self-employed. As a result both the ratio of high to low educated and paid employment to self-employment fall.

In HRA, increased R&D causes a net increase in employment, both among the low educated and the high educated. Two local composition effects explain the positive employment impact. First, positive employment change occurs in construction and non tradeable services (such as trade, accommodation and food and public sector, education and creative industries) and in finance and business services, whereas manufacturing employment shrinks. Second, all the employment created is self-employment (paid employment decreases).

We investigate the nature of the increase in self-employment as a result of increased R&D 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 opportunities it may create through spillovers, or reallocation because workers are left without paid employment.

Taking together the results, R&D in LRA has a small negative impact on employment levels, but changes the composition towards more educated workers in manufacturing industries. Instead, in HRA an increase in R&D has a positive impact on employment levels, but changes the composition towards less educated workers, mainly in non tradeable and personal services, and among the self-employed. 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.

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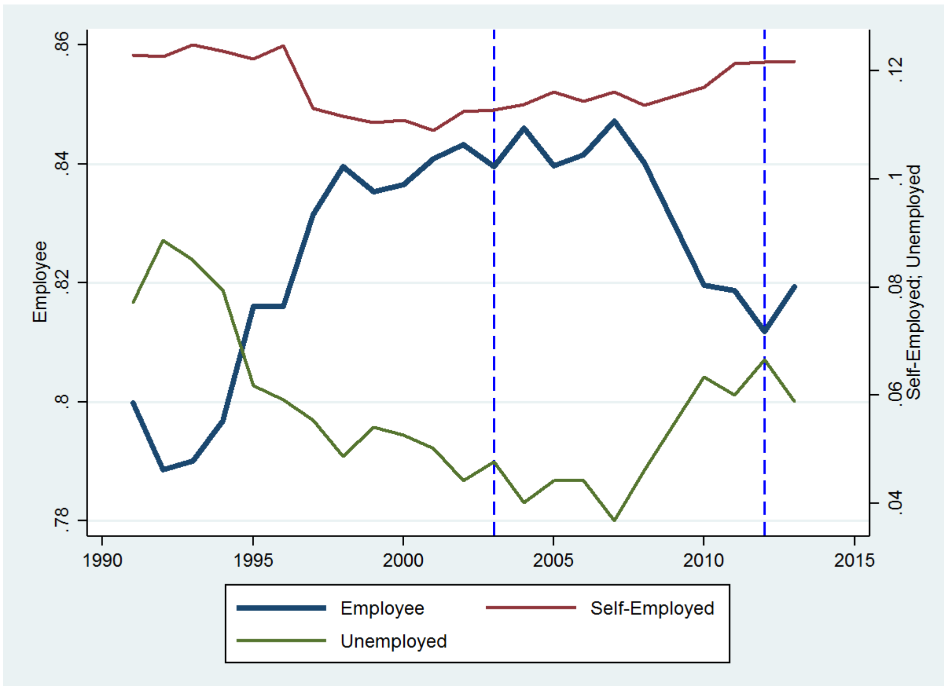
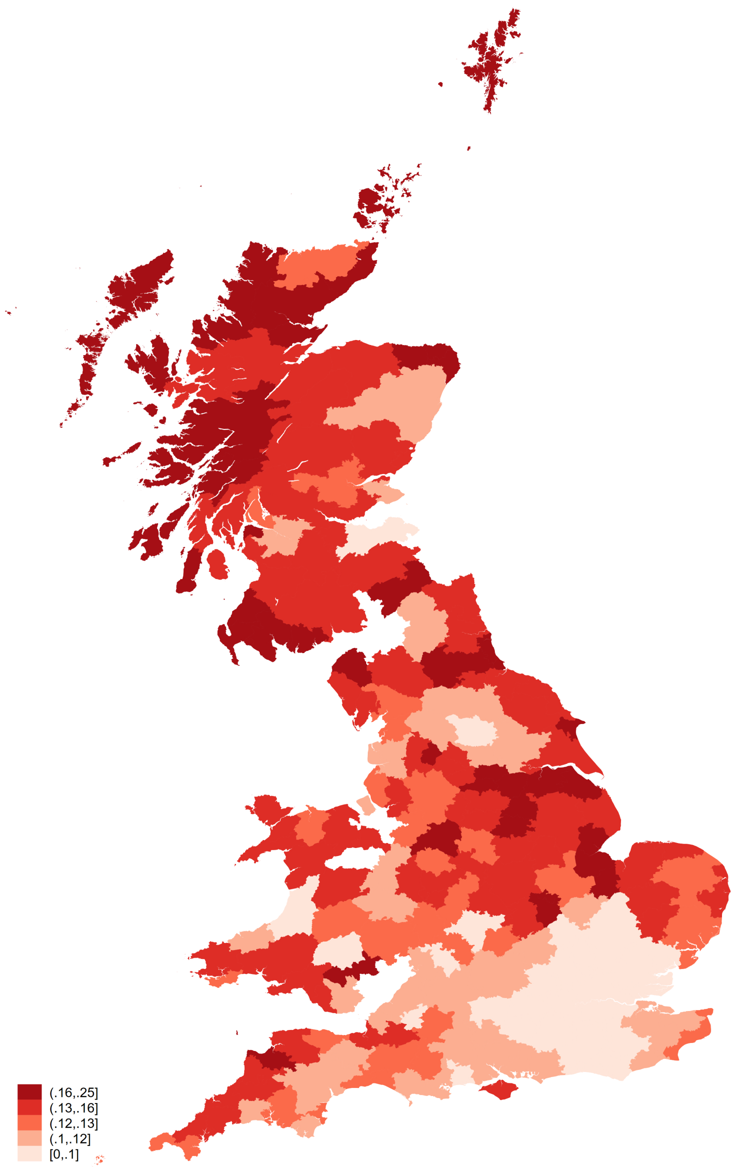
A Figures

Figure 1: Trends of Employment, Unemployment and Self-Employment in the UK, 1991-2013



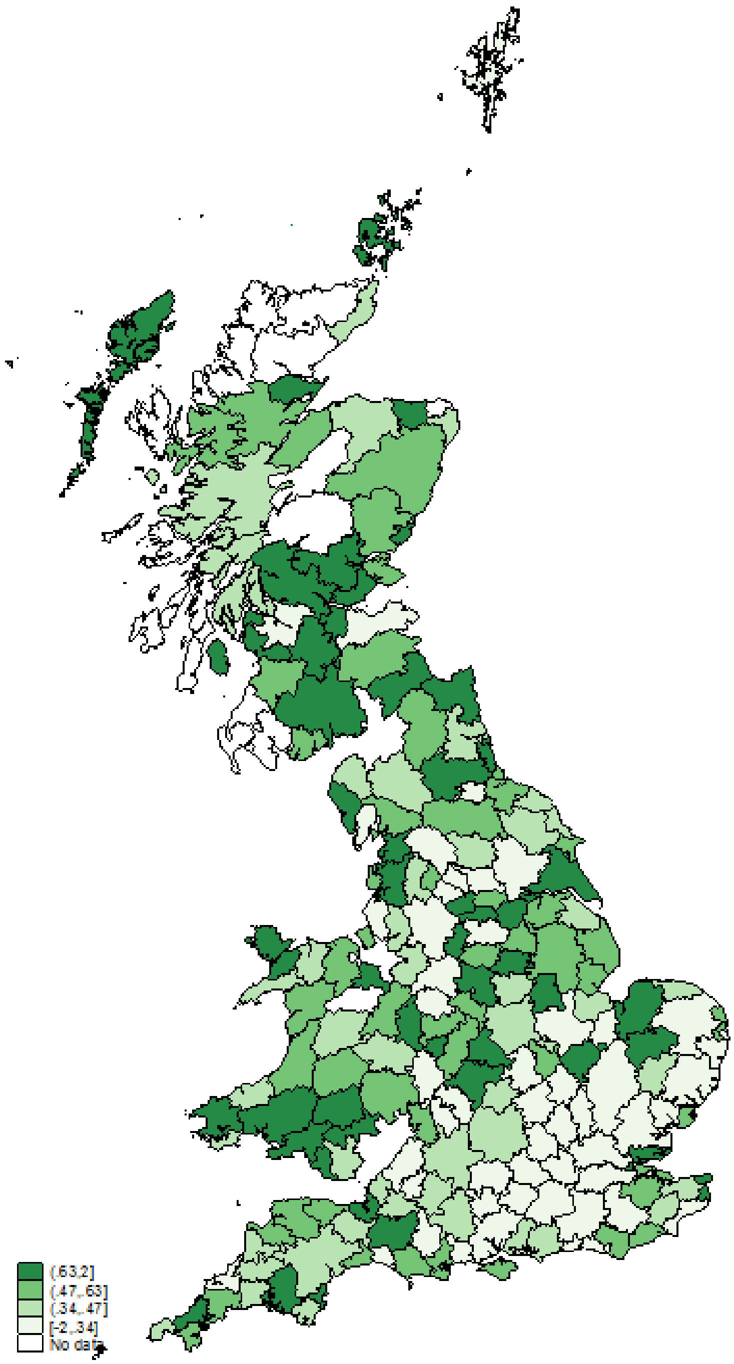
Source: own elaboration based on date from the British Household Panel Survey (BHPS)

Figure 2: Share of Routine Employment across British TTWAs, 2001



Each TTWA reports the labor share of category NS-Sec 7, *Routine Occupations*.

Figure 3: R&D investments across British TTWAs, 2001



Own elaboration based on BERD

B Tables

Table 1: 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 1: [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 2: Baseline results

	Baseline	Initial routinisation
	Ln(E)	Ln(E)
	(1)	(2)
a. Bartik shift-share IV		
ΔRD	-0.07***	-0.09***
	(0.01)	(0.02)
$\Delta RD \times \phi$		0.15***
		(0.05)
Obs.	212	212
b. Trade Induced IV		
ΔRD	-0.06***	-0.08***
	(0.01)	(0.01)
$\Delta RD \times \phi$		0.08***
		(0.02)
Obs.	212	212

Notes to table 2: [1] All dependent variables are log changes in the TTWA from 2001 to 2011; Ln(E) is total employment. [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 3: The effect of R&D on employment, by education

	High Ln(H) (1)	Low Ln(L) (2)	Ratio Ln(H/L) (3)
a. Baseline			
ΔRD	0.15***	-0.02**	0.17***
	(0.01)	(0.01)	(0.01)
Obs.	212	212	212
b. By TTWA routinisation			
ΔRD	0.17***	-0.05***	0.22***
	(0.01)	(0.01)	(0.01)
$\Delta RD * \phi$	0.00	0.09***	-0.09
	(0.10)	(0.03)	(0.08)
Obs.	212	212	212

Notes to table 3: [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 education = level 4 or more for England and Wales, and levels 3 or above for Scotland. Low education = any lower than high education. [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 takes 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 4: 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***	-0.13***	0.26***	-0.06***	0.10***	-0.03***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
Obs.	212	212	212	212	212	212
b. By TTWA routinisation						
ΔRD	0.40***	-0.21***	0.18***	-0.09***	0.04	-0.07***
	(0.01)	(0.04)	(0.05)	(0.02)	(0.03)	(0.03)
$\Delta RD * \phi$	-0.85***	0.65***	0.59*	0.26***	0.42**	0.27**
	(0.17)	(0.10)	(0.34)	(0.02)	(0.20)	(0.13)
Obs.	212	212	212	212	212	212

Notes to table 4: [1] All dependent variables are log changes in the number of employed individuals within each TTWA 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 takes 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 5: The effect of R&D on paid employment and self-employment

	By Emp. Type			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	-0.05***	-0.16***	0.11***	0.31***	0.20***	0.07***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)
Obs.	212	212	212	212	212	212
b. By TTWA routinisation						
ΔRD	-0.05***	-0.25***	0.20***	0.49***	0.32***	0.11***
	(0.01)	(0.03)	(0.02)	(0.03)	(0.04)	(0.01)
$\Delta RD * \phi$	0.06	0.70***	-0.64***	-1.33***	-0.94***	-0.33***
	(0.05)	(0.10)	(0.07)	(0.21)	(0.16)	(0.04)
Obs.	212	212	212	212	212	212

Notes to table 5: [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 6: Self-Employment by type of self-employment

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

Notes to table 6: [1] All dependent variables are log changes in the TTWA from 2001 to 2011 in the number of self-employed individuals grouped in 4 categories: with employees (total: col. 1) (part- (col. 2) and full-time (col. 3)) and without employees (total: col. 4) (part (col. 5) and full time (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 smooth short run fluctuations. 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 takes 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). Differently from previous tables, sector shares are computed using turnover rather than employment (we are waiting for full data release). [7] Small differences between these estimates (col. 1) and aggregate estimates in Table 12 (col. 2) are because in Table 12 we could exclude students; we cannot exclude students when disaggregating by full-time and with or without employees. The stock and flow of aggregate figures, with and without students, is similar. [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.

C Extra Tables

Table 7: 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 8: Employment composition by sector

	2001	2011	Change
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 8: [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.

C.1 Bartik Shift-Share Instrument Using Turnover

Table 9: Baseline results

	Baseline	Initial routinisation
	Ln(E)	Ln(E)
	(1)	(2)
a. Bartik shift-share IV		
ΔRD	-0.08***	-0.11***
	(0.01)	(0.03)
$\Delta RD \times \phi$		0.20***
		(0.08)
Obs.	212	212

Notes to table 9: [1] All dependent variables are log changes in the TTWA from 2001 to 2011; Ln(E) is total employment. [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 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). [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: 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 to table 10: [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 education = level 4 or more for England and Wales, and levels 3 or above for Scotland. Low education = any lower than high education. [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 takes 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 11: 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 11: [1] All dependent variables are log changes in the number of employed individuals within each TTWA 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 takes 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 12: The effect of R&D on paid employment and self-employment

	By Emp. Type			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.

C.2 Trade Induced Instrumental Strategy (not included in the main text)

Table 13: The effect of R&D on employment, by education

	High Ln(H) (1)	Low Ln(L) (2)	Ratio Ln(H/L) (3)
a. Baseline			
ΔRD	0.11***	-0.02***	0.13***
	(0.01)	(0.00)	(0.01)
Obs.	212	212	212
b. Interaction: slope			
ΔRD	0.10***	-0.09***	0.19***
	(0.01)	(0.02)	(0.02)
$\Delta RD \times \phi$	0.02	0.27***	-0.26***
	(0.03)	(0.04)	(0.07)
Obs.	212	212	212

Notes to table 13: [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 education = level 4 or more for England and Wales, and levels 3 or above for Scotland. Low education = any lower than high education. [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 takes 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 US industries exposition to Chinese imports in 2001 (trade induced 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 14: The Effect of R&D on employment, by industry

	Manufacturing	Construction	Transport	Wholesale, retail	Business and	Public sector and entert.
	(1)	(2)	(3)	(4)	(5)	(6)
a. Baseline						
ΔRD	0.17***	-0.05***	0.28***	-0.04***	0.11***	0.06***
	(0.04)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)
Obs.	212	212	212	212	212	212
b. Interaction: slope						
ΔRD	0.27***	-0.18***	0.06*	-0.07***	0.03**	0.13***
	(0.06)	(0.02)	(0.04)	(0.00)	(0.01)	(0.02)
$\Delta RD \times \phi$	-0.35***	0.48***	0.82***	0.10***	0.30***	-0.27***
	(0.06)	(0.07)	(0.10)	(0.01)	(0.02)	(0.08)
Obs.	212	212	212	212	212	212

Notes to table 14: [1] All dependent variables are log changes in the number of employed individuals within each TTWA 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 takes 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 US industries exposition to Chinese imports in 2001 (trade induced 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 15: The effect of R&D on paid employment and self-employment

	By Emp. Type			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	-0.05***	-0.10***	0.05***	0.15***	0.11***	0.03***
	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.01)
Obs.	212	212	212	212	212	212
b. Interaction: slope						
ΔRD	-0.05***	-0.20***	0.14***	0.31***	0.25***	0.05
	(0.01)	(0.03)	(0.04)	(0.07)	(0.06)	(0.03)
$\Delta RD \times \phi$	0.03*	0.36***	-0.33***	-0.59***	-0.54***	-0.07
	(0.01)	(0.07)	(0.08)	(0.16)	(0.14)	(0.08)
Obs.	212	212	212	212	212	212

Notes to table 15: [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 US industries exposition to Chinese imports in 2001 (trade induced 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 16: 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	-0.09***	-0.14***	-0.11***	-0.14***	-0.02	0.05**	-0.03***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
Obs.	212	212	211	212	212	212	212
b. Interaction: slope							
ΔRD	-0.17***	-0.24***	-0.29***	-0.23***	-0.11***	-0.00	-0.16***
	(0.03)	(0.02)	(0.06)	(0.01)	(0.04)	(0.06)	(0.04)
$\Delta RD \times \phi$	0.30***	0.39***	0.66***	0.33***	0.36***	0.20*	0.47***
	(0.05)	(0.04)	(0.13)	(0.03)	(0.08)	(0.12)	(0.07)
Obs.	212	212	211	212	212	212	212

Notes to table 16: [1] All dependent variables are log changes in the TTWA from 2001 to 2011 in the number of self-employed individuals grouped in 4 categories: with employees (total: col. 1) (part- (col. 2) and full-time (col. 3)) and without employees (total: col. 4) (part (col. 5) and full time (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 smooth short run fluctuations. 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 takes 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 US industries exposition to Chinese imports in 2001 (trade induced type IV). [7] Small differences between these estimates and aggregate estimates in Table 15 are because in Table 12 we can exclude students; we cannot exclude students when disaggregating by full-time and with employees. The stock and flow of aggregate figures, with and without students, is close. [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.