Do low-skilled workers gain from high-tech employment growth? High-technology multipliers, employment and wages in Britain

Neil Lee[a,*], Stephen Clarke[b]

[a] Department of Geography and Environment, London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, United Kingdom
[b] The Resolution Foundation, Queen Anne's Gate, London, SW1H 9AA, United Kingdom

ABSTRACT

Do low-skilled workers benefit from the growth of high-technology industries in their local economy? Policymakers invest considerable resources in attracting and developing innovative, high-tech industries, but there is relatively little evidence on the distribution of the benefits. This paper investigates the labour market impact of high-tech growth on low and mid-skilled workers, using data on UK local labour markets from 2009–2015. It shows that high-tech industries – either STEM-intensive 'high-tech' or digital economy – have a positive jobs multiplier, with each 10 new high-tech jobs creating around 7 local non-tradeable service jobs, around 6 of which go to low-skilled workers. Employment rates for mid-skilled workers do not increase, but they benefit from higher wages. Yet while low-skilled workers gain from higher employment rates, the jobs are often poorly paid service work, so average wages fall, particularly when increased housing costs are considered.

1. Introduction

High-technology industries are seen as vital for economic development, and policymakers invest considerable resources in attracting and growing the sector (e.g. Youtie and Shapira, 2008; Brown and Mason, 2014). Workers in tech tend to be highly-skilled and well-paid. But what impact do these innovative industries have on the living standards of low-skilled workers? The literature essentially takes two positions on the broad economic effects of tech (Lee and Rodríguez-Pose, 2016). Studies focused on job creation have tended to be positive, based on the idea that high-technology is a tradeable sector and so has a 'multiplier effect' creating jobs in non-tradeable sectors in the same local economy (North, 1955; Tiebout, 1956). In particular, Moretti's (2010; 2013) work has highlighted potentially large multipliers from high-technology industries: in his research, each additional job created in high-tech creates between 4–5 new jobs in the non-tradeable service sector. Based, at least in part, on this evidence, policymakers often aspire to transform their local economies into high-tech hubs. For example, in 2011, then UK Prime Minister David Cameron (2011: 1) argued that "In

the UK, we are creating a tech hub, a Silicon Valley of our own in East London".

Yet others have questioned this optimistic view. A pessimistic literature investigates the extent to which economic development strategies focused on high-technology industries benefit local workers (Bartik, 1991; Goetz et al., 2011; Breau et al., 2014; Kemeny and Osman, 2018; Echeverri-Carroll et al., 2018). Studies of cities with strong high-tech economies have highlighted the problems of inequality and polarisation which might result. For example, Saxenian (1983) notes the problem of low-wage service work in Silicon Valley. Similarly, Florida (2005) highlighted growing inequality in high-technology cities between affluent workers in advanced sectors and the low-wage workers in personal services nearby, and more recently has expressed concern about a 'new urban crisis' in the most innovative cities (Florida, 2017). Essentially, this literature suggests that while growth in skilled tech employment may create new jobs for less skilled workers, these jobs are not all well-paid and high housing costs will further reduce living standards (Florida, 2017). Silicon Valley's economic success has come at the cost of high inequality, low wage employment, and high

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* Corresponding author.
  E-mail address: n.d.lee@lse.ac.uk (N. Lee).

housing costs. In short, there is a dark side to high-tech growth: benefits to skilled workers, but with low-skilled workers losing out.

Despite this potential 'dark side', UK policymakers have been enthusiastic in their support for high-tech industries (see Foord, 2013). This was particularly the case following the financial crisis of 2009. Concerned about the economy's focus on finance, the UK government attempted to rebalance the economy to other sectors (Berry and Hay, 2016). A set of 'Catapult Centres' were launched, modelled on the German Fraunhofer Institutes with the aim of developing commercial collaborations between business and scientists (Kerry and Danson, 2016). In London, the legacy of the 2012 Olympics was partly focused on a new science campus, while a cluster of high-tech firms near Shoreditch was branded 'Tech-City' (Nathan and Vandore, 2014). Other cities benefited from investments such as Manchester's Science Park and new research institutes focused on commercially viable research (Lee, 2017). Regardless of whether these efforts were successful, the post-crisis period also provided relatively favourable conditions for growth in the sector. New technologies such as smartphones diffused into the regular economy and provided new opportunities at a time when the national economy was weak. The result was a relatively strong growth performance in much of the tech sector.

What is the impact of the growth in high-technology employment on low skilled workers in the local economy? This is an important question, given both government investments in the sector and its likely future growth. Empirical work tends to be relatively polarised between the multipliers literature, which tends to highlight job creation (Moretti, 2010; Moretti and Thulin, 2013; Van Dijk, 2017) and the literature on wages which focuses on the problems of inequality and low wage work in the context of high housing costs (Echeverri-Carroll and Ayala, 2009; Breau et al., 2014; Lee and Rodríguez-Pose, 2016; Florida, 2017; Kemeny and Osman, 2018). Yet, to the best of our knowledge, these studies have focused on the extreme example of the United States and tended to either focus on jobs *or* wages. Moreover, most definitions of 'high-tech' have tended to ignore the digital economy firms which dominate narratives of the sector.

This paper addresses these gaps by considering the economic impact of high-technology industries on less-well educated workers in 182 British local labour markets between 2009–2015. Our focus is on two core parts of 'tech': STEM-intensive high-technology industries, which includes a broad and diverse set of industries including some oil and gas and pharmaceuticals (Bakhshi et al., 2015), and the digital economy sector which is focused on new digital technologies (Office of National Statistics, 2015). We adapt the multiplier models used by Moretti (2010) and test the impact of these industries on employment for less educated groups, alongside fixed effects panel models considering the impact on wages. The results suggest a positive jobs multiplier from high-technology sectors, but that the effect is smaller than in US evidence. The jobs multiplier increases employment rates for less-well educated workers with no 'crowding out' of tradeable industries. However, there is some evidence that growth in tech is associated with reductions in the average wage for less well-educated workers, suggesting new jobs are not well paid, a problem slightly worsened by higher housing costs in successful high-tech local economies.

Our paper makes two main contributions to the literature. Firstly, studies are largely US-focused with less evidence from countries with weaker high-tech economies. Moreover, they focus on the pre-crisis period, with no evidence on multipliers in the sluggish labour markets of most developed economies since – a significant omission given the weak wage growth since 2007 (Machin, 2015). Secondly, studies tend to focus on either job creation (e.g. Moretti and Thulin, 2013) or wages (e.g. Lee and Rodríguez-Pose, 2016) with little work testing both. These omissions are particularly important for innovation studies, given the importance of spatially targeted investments in high-technology as an innovation policy tool (Brown and Mason, 2014) and growing interest in how innovation-intensive growth can be made inclusive (see Stilgoe et al., 2013; Zehavi and Breznitz, 2017). A further contribution is the

use of more precise definitions of high-technology than existing work. We include one relatively broad definition, but extend this to include an indicator of 'digital economy' which will capture other parts of the high-tech economy.

The paper is structured as follows. Section 2 sets out the basic framework for analysis in the literature on multipliers and extends it to consider the impact on the living standards of local workers. Section 3 outlines the data on both sectors and local labour markets which will be used to test these predictions. Section 4 presents models for jobs growth. Section 5 extends this to consider wages and the mechanisms through which they might change. Section 6 concludes with implications for theory and policy.

2. Theoretical background

2.1. Job multipliers from high-technology industries

The idea of local multipliers from tradeable industries is one of the most important theories in urban and regional economics. It has a long history (see O'Sullivan, 2003 for a textbook example), but has been popularized by recent work by Moretti (2010; 2013) and Moretti and Thulin (2013). The basic multiplier framework divides economic activity into two types: *non-basic production*, such as retail, restaurants, personal services or construction, which services local demand; *basic or tradeable production*, such as manufacturing or tradeable services, which creates local demand. An exogenous shock to the tradeable sector – such as the successful commercialization of a new product – has knock-on impacts on the local economy. The initial benefit to the tradeable sector then leads to a "multiplier effect" in the local economy, largely in non-tradeable sectors. For example, if a high-tech firm is created in an area, the local economy benefits from the spending of the firm and the spending of workers, and this leads other local industries to benefit.

Several factors determine the size of the multipliers. The first is the sector itself – its supply chain and impact on other local sectors. Some high-technology industries may aid growth in other local sectors, for example by employing lawyers or consultants. Others may be relatively disengaged from local supply chains. Some advanced industries may play a role in stimulating innovation in other sectors via input-output linkages (Bakhshi and McVittie, 2009; Isaksson et al., 2016), and this might happen locally. The second impact comes from the local spending of the workers in tradeable industry. Well-paid, high-skilled workers in industries like tech have more money to spend locally than less well-paid workers (Moretti and Thulin, 2013).

High-technology industries are seen as having particularly large multipliers. Moretti (2010; 2013) argues that the standard multiplier effect ignores the potential benefits of high skilled employment on job creation, and productive sectors with high salaries can have a disproportionate local impact. His research on US cities suggests that each additional job in high-tech industries – defined as Machinery and Computing Equipment, Electrical Machinery and Professional Equipment – is associated with an additional 4–5 jobs in the rest of the local economy over the next ten years. High-technology industries have a combination of well paid, skilled jobs, and strong supply chains, which might mean they have a disproportionate impact on regional economies. They are likely to produce many of the most significant innovations in the new economy. Other studies have come to similar conclusions. For example, Gitell et al. (2014) find that growth in the high-tech sector is an important determinant of total employment growth.

2.2. High-technology, wages and costs

While the literature on job creation tends to focus on the benefits of high-tech growth, fewer studies have directly considered the distribution of the gains (Lee and Rodríguez-Pose, 2016). Yet at least three literatures have highlighted the relationship between concentrations of

high-skilled workers in innovative sectors and personal service jobs. Studying global cities, Sassen (2001) notes the importance of a low-wage service class of cleaners, security guards and other personal service workers close to the affluent workers in finance and other advanced sectors. Similarly, the literature on skills-biased technological change has highlighted the growth in these low wage service jobs to fulfil functions outsourced by the affluent, but time poor, workers whose incomes have been boosted by new technology (Autor and Dorn, 2013). Empirical studies of human capital multipliers come to similar conclusions: Kaplanis (2010a; 2010b) shows that an increase in the share of skilled workers in a travel-to-work area is associated with higher wages and probabilities of employment for low skilled workers.

In the general equilibrium model of a regional economy, growth in one sector may have knock-on impacts on the rest of the regional economy (Moretti, 2011). Moretti (2011) describes this situation in detail. To summarise, an exogenous shock - such as a commercially successful innovation - will increase productivity locally. This productivity shock will provide an incentive for workers to move to the more productive local labour market. But in-migration causes an increase in the demand for housing, which is limited in supply. Part of the benefits of the productivity shock go to labour, part to land or property owners. In the extreme case that land supply is perfectly fixed, all of the benefits go to landowners. Any increase in land and labour costs will have a second order effect in the local economy. Growth in non-tradeables will depend on the balance of these costs against the increased demand. For tradeables, which may not benefit from increased local demand, there will be an increase in costs. Because of this, growth in high-tech may squeeze out other tradeable sectors in the local economy.

There is some empirical evidence to support this 'squeezing out' effect. Faggio and Overman (2014) consider the impact of public sector growth on local employment, finding each additional public-sector job creates 0.5 jobs in the non-tradeable service sector (services and construction), but comes at a cost of 0.4 jobs in other tradeable employment in manufacturing. If these compositional effects do apply locally, the impact will depend on the type of jobs which are created and destroyed. Tradeable jobs tend to be better paid than non-tradeables, with manufacturing in particular seen as offering well paid employment for relatively less well-educated workers (Sissons et al., 2018). Growth in tech might squeeze some of these jobs out, but replace them with relatively low paid personal service work.

Other theoretical work has highlighted the potential of knowledge spillovers from high-technology industries to other parts of the urban economy (Fallah et al., 2014). For example, Winters (2014) shows external wage effects from graduates in Science, Technology, Engineering and Maths (STEM) into other parts of the local economy, and argues that this represents a form of human capital spillover. Workers in other sectors may learn from skilled, innovative workers with STEM skills. Similar processes may operate from high-tech industries which often have, almost by definition, high shares of STEM employment. In these cases, workers will gain from higher productivity, which will then increase their wages.

In short, high-technology may influence wages for other workers in a number of ways, primarily: (1) by changing the sectoral or occupational composition of the local labour market, for example through new job creation in personal services or by squeezing out manufacturing, (2) by increasing labour demand more generally, or (3) by increasing worker productivity, through learning or knowledge spillovers.

However, there is relatively little empirical work on high-technology industries and the wage distribution. One problem is that of disentangling the impact of high-tech growth from other potential drivers of local employment or wage changes. Studies tend to use an instrumental variable approach to address this. For example, Echeverri-Carroll and Ayala (2009) use a cross-section and to show that workers in a high-tech city earn a premium of around 4.6%, but that the premium is higher for high than low skilled workers. Their instrument is

the presence of a land-grant university. In a panel study using a Bartik style shift-share instrument, Lee and Rodríguez-Pose (2016) consider the impact of tech employment in US metropolitan statistical areas on the wage distribution and poverty rates. They find that tech employment is associated with increased wages for less well-educated workers, but that the benefits accrue to those with incomes around double the poverty line and do not trickle down to those in poverty. Although they do not always consider causality, studies on the relationship between innovation and inequality tend to find a positive link between the two, although they do not assess whether this is because of high incomes or wages at the top of the distribution, or lower wages at the bottom (see Lee, 2011; Lee and Rodríguez-Pose, 2013; Breau et al., 2014). In related work, Ciarli et al. (2018) show that local Research and Development (R&D) activity has no local multiplier effect, but does change the composition of employment in UK TTWAs. The effect depends, however, on the initial structure of the local economy.

Case study evidence suggests significant problems in cities with strong high-tech economies. The evidence is focused on the extreme case of Silicon Valley. Saxenian (1983: 256) argued that high-technology had "transformed the local class structure" where:

"Semiconductor production generated a bifurcated class structure in the county, one which was distinguished by a large proportion of highly skilled engineers and managerial personnel alongside an even larger number of minimally skilled manufacturing and assembly workers

But the division in more recent studies is more often between those working in the sector, and those in personal service occupations which support it. For example, Donegan and Lowe (2008) show that high-tech cities are more unequal, and suggest that poorly paid personal service work may be to blame. Yet while these studies suggest a relationship, they do not test the causal impact of high-tech growth on low-wage jobs. In the remainder of the paper, we set out to address this.

3. Data and descriptive statistics

3.1. Spatial units

Our units of analysis are Travel to Work Areas (TTWAs). Developed by Coombes (2015) and the Office of National Statistics (2015), TTWAs are probably the most commonly used functional economic units for the United Kingdom. They comprise relatively self-contained local labour market areas, with the basic definition of around 75% self-containment with at least three quarters of the local workforce also living in the area and a minimum economically active population of 3,500 (Office of National Statistics, 2016). Using these commuting zones should minimize 'leakage' of any multiplier outside the local economy (Gordon, 1999; Gordon and Turok, 2005). According to the Coombes calculations, there are 212 TTWAs in Great Britain, 160 of which had populations of greater than 60,000 in 2011. Northern Ireland is sadly excluded because the local level data we use is not published at local authority level there.

While the TTWAs are defined using very small geographical units, the wage and skills data used in this paper is only available for larger Local Authority (LA) areas.[1] To match the two geographies we construct a new set of TTWAs where LA is allocated into the TTWA with which it has the largest physical overlap. Testing shows that this provides a good approximation of Coombes' TTWAs, with the exception of London which has a large green belt and so loses a significant number of outer boroughs. To address this, we use the official Greater London Authority area as London's TTWA. The result is that we have fewer

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[1] More precisely: the TTWAs are defined using Lower Level Super Output Areas (LSOAs), but the Annual Population Survey – used for the wage and individual data – is only available at the Local Authority level. To ensure these are as detailed as possible, we use the boundaries from before the 2009 LA reorganisation which reduced the number of LAs.

TTWAs than Coombes with a larger average size and far fewer very small TTWAs.[2]

3.2. Defining high-technology industries

The main source of data for employment is the Business Register and Employment Survey (BRES), a local-level employment survey in the UK and the official government source of employment estimates. Information is collected from businesses across the UK as a whole, with around 80,000 firms sampled each year from a population of around 2 million.[3] Data is for employees and business owners (such as partners in a company, or sole proprietors). However, it misses businesses not registered for either Value Added Tax (VAT) nor Pay as You Earn (PAYE) and so the vast majority of self-employed people. While the raw source of the BRES data begins much earlier, our choice of relatively fine sectoral definitions means our data begins in 2009, when the 2007 Standard Industrial Classification (SIC) code definitions were applied.

The BRES data allows analysis at the relatively fine sectoral level of four-digit SIC codes. We use it to construct our dependent variable: non-tradeable employment. The definition for non-tradeables is an adaptation of that used by Jensen and Kletzer (2006) and Faggio and Overman (2014).[4] Essentially, this methodology assumes that economic activities which are broadly geographically dispersed are untradeable; those which are highly concentrated are tradeable. The distinction between tradeable and non-tradeable industries is not binary, so to ensure our results are relatively clear we choose a relatively tightly defined set of industries which correspond to the most geographically dispersed category produced by Jensen and Kletzer. This includes construction and a set of non-tradeable services (sale and repair of motor vehicles; retail; hotels and restaurants; some financial intermediation; some real estate, renting and business activities, and other community activities). These industries are all relatively geographically widespread, and so we assume they cannot be easily traded over long distances. Full codes are given in table A1 in the appendix.[5]

There is no single definition of high-technology industries. The most commonly used definition comes from Hecker (2005) who proposes three potential definitions of high-technology: (1) based on share of R&D employment, (2) use of high-technology production, or (3) production of high-technology products. Studies focused on the United States such as Fallah et al. (2014) and Lee and Rodríguez-Pose (2016) use a definition based on Hecker's (2005: 58) categorisation which was based on the "science, engineering, and technician occupation intensity" of the industry. However, this US-focused definition may not reflect the UK's industrial structure (as different industries may be tech-intensive) and there may be problems mapping it onto SIC codes.

Our definition instead comes from the replication of Hecker conducted by Bakhshi et al. (2015) who comprehensively review definitions of the high-tech economy and construct a new set of indicators based on the SIC 2007 codes for which BRES data is available. Bakhshi et al. (2015) adapt Hecker's approach in the following manner. They begin by defining a similar set of Science, Technology, Engineering and Maths (STEM) occupations to those used by Hecker.[6] They then select all industries with STEM employment above a threshold of 15% of total, on the basis that this seems to provide a justification for a set of industries which is both similar to the commonly used Eurostat high-technology definition (but more detailed) and also similar to that given by Hecker for the United States. The result is a set of STEM-intensive, high-technology industries which includes much of pharmaceuticals, high-technology manufacturing (such as consumer electronics), but also technical industries related to resource extraction such as pipelines. We make one minor change, excluding 'reinsurance' as it seems relatively distinct in spirit from the other high-technology industries in the list. The full list of included SIC codes is given in table A2 in the appendix. Overall, we refer to this industry as "*high-technology*".

One significant concern with this definition is that - while it is both rigorously defined and close to the measures used in other studies - it missed some industries which are commonly considered 'tech'. To address this problem, we define a second category of industries based on the OECD definition of the digital economy which is used by the UK government (see Office of National Statistics, 2015; Department of Culture, Media and Sport, 2016). This includes some computer manufacturing, but also software development, web portals, and other ICT intensive activity. Any digital economy firm which forms part of Bakhshi's definition of 'high-tech' becomes digital economy. Full definitions are given in Appendix A. We term this '*digital economy*'.

The analysis is focused on the aggregation of these two industries, *high-tech and digital economy*. On average, just under 7 percent of employment in British cities is in these sectors, a figure which changes little between the two periods.

3.3. Wages and employment

We use a second dataset, the Annual Population Survey (APS), to construct variables for wages by skill group, employment rates, and self-employment. The APS is a rolling quarterly labour market survey (Office for National Statistics, 2017). It is focused on individual labour market activity, and the survey contains good information on employment situation, occupation and sector, wages, education and other personal characteristics such as age and gender. The APS aims to have a sample of at least 510 economically active people in each Local Authority, and so allows analysis of labour market characteristics at a local level with some precision (Office for National Statistics, 2017). We use the annual data for January to December, which gives around 190,000 observations of working age individuals.

We use the APS to calculate initial control variables and variables for employment rates and wages. As the focus of this paper is on benefits to low and mid-skilled workers, we use the APS to divide our data into three skill groups. The UK population is seeing a long-term increase in skill levels, which is being reflected in the labour market and may change definitions of 'low skill' based solely on qualifications (for example, apprenticeships provision expanded significantly in the period in question, while the average quality has fallen). At the same time, educational standards are closely associated with age meaning that there may be biases depending on the age profile of TTWAs. To account

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[2] Note that experimentation using 2001 TTWA boundaries leads to very similar results.

[3] This is roughly a 4% sample of the business stock. The source is generally used as the best available measure of the UK business stock locally.

[4] This adaptation is for 2003 SIC codes, so we adapt it for 2003 SIC codes to use for 2007 SICs. This does not seem to involve a significant loss of detail.

[5] We remove one industry – Wired telecommunications activity – from the definition of non-tradeables because it also falls in our definition of 'tech'.

[6] They note that they exclude 'a number of technician roles' which Hecker includes (pp. 32) and exclude a small number of industries with small sample sizes in occupational data. These are as follows (with SOC codes in parenthesis). *Engineering*: Civil Engineers (2121), Mechanical Engineers (2122), Electrical Engineers (2123), Electronics Engineers (2124), Design and Development

(footnote continued)
Engineers (2126), Production and Process Engineers (2127), Engineering Professionals n.e.c. (2129), and Chartered Surveyors. *Information Technology:* Information technology and telecommunications directors (1136), IT specialist managers (2133), IT business analysts, architects and systems designers (2135), Programmers and software development professionals (2136), Web design and development professionals (2137), Information technology and telecommunications professionals (2139). *Science:* Chemical scientists (2111), Biological scientists and biochemists (2112), Physical scientists (2113), Natural and social science professionals n.e.c. (2119), Conservation professionals (2141), Environment professionals (2142), Research and development managers (2150), Actuaries, economists and statisticians (includes mathematicians) (2425).

for this, we divide all those aged 18–64 into three roughly equally-sized groups on the basis of the ranking of their qualifications: skilled workers, most of whom are qualified to degree level or above; mid-skilled workers, with better than General Certificate of Secondary Education (GCSE) qualifications (a set of qualifications normally taken at age 16, after around 11 years of education); and, low skilled workers who have either poor GCSEs or no qualifications. Where educational categories overlap two 'thirds' we randomly allocate into one or the other. As the focus is on the external benefits of high-technology sectors, we also exclude workers in high-technology and digital economy from indicators using these skill groups.

We also use APS to construct indicators of self-employment. BRES does not include the vast majority of self-employed workers, yet around 45% of UK employment growth between the 2008 recession and 2015 was in self-employment (Tomlinson and Corlett, 2016). Much of the growth was in non-tradeable sectors such as driving or construction (see Ciarli et al., 2018 for more evidence on this). To account for this, a measure of non-tradeable self-employment is also added to the BRES figures, giving a variable for total employment and self-employment in non-tradeables.

In a simple descriptive analysis, the two measures of high-tech and digital economy employment growth and non-tradeable employment and self-employment seem closely related. Fig. 1 shows scatter plots of the relationship between growth in overall high-technology and growth in non-tradeable employment (local services and construction) on the other. It shows a clear positive relationship between growth in high-technology and digital economy and growth in non-tradeables and self-employment.

4. Model and results

4.1. Empirical strategy

Our first models focus on changes in employment. For these, we follow Moretti (2010) and estimate adapted models of the form:

$$\triangle NonTrade_c = \alpha + \beta_1 \triangle Tradeable_c + \gamma \, X_c + \varepsilon_c \qquad (1)$$

where, $\triangle NonTrade_c$ is the change in the log number of non-tradeable jobs and self-employment in TTWA 'c' between 2009–2015, $\triangle Tradeable_c$ is the change in the log number of tradeable high-tech jobs in TTWA 'c' in the same period, the vector X accounts for initial TTWA characteristics which will affect future non-tradeable employment growth, and ε is the error term. The key figure of interest is the coefficient β on high-tech industries. If β is positive, this indicates that growth in high-technology is associated with growth in non-tradeables.[7] Essentially, we are interested in whether growth in high-tech industries in the period lead to changes in the number of non-tradeable jobs.[8]

One concern is that initial conditions may be correlated with both growth in non-tradeables and share of tradeables so, following Faggio and Overman (2014), we add a series of controls. First, skill levels are an important predictor of economic success. A variable for the share of the population qualified in the top third of the national population (roughly degree or medical professional level or above) is used. Secondly, we control for initial economic conditions and the available labour force using the unemployment rate. This should be negatively

Fig. 1. High-technology industries versus non-tradeables employment. 2009–2015.
Source: BRES, APS, and authors' adaptation. Each dot represents one of 182 travel-to-work areas.

associated with subsequent employment growth. Third, to control for potential agglomeration economies we use the log of total employment. If larger areas produced more jobs in the period, we expect this to be positive. In addition, we include regional dummies for the 11 Government Office Regions. These should control for unobserved region-specific factors and differential policy in Wales and Scotland, it also allows us to partially filter out initial regional differences in high-tech employment. Summary statistics on the variables used are given in Table 1.

4.2. Instrumental variables

The key problem with this model is endogeneity. Some sort of idiosyncratic shock may affect both growth in high-tech employment and non-tradeables. This is quite plausible in the time period we investigate. For example, the UK government launched a series of research centres in the early 2010's which were designed to stimulate growth in high-technology or digital economy industries, but which were likely also to impact on non-tradeable employment. This would result in a positive correlation between high-tech and non-tradeables, biasing upwards the size of the coefficient.

To address this problem, we use two instrumental variables (IVs). The first is a shift-share instrument which builds on Bartik's (1991) seminal book and has become relatively standard in the literature (for example, Moretti, 2010; Faggio and Overman, 2014; Lee and Rodríguez-Pose, 2016; Van Dijk, 2017). Our instrument is calculated using predicted employment growth in each sub-sector based on initial local shares in each industry we focus on (in 2009) and national growth rates over the subsequent period.[9] Simply, we take initial employment in the digital economy sector and assume that the sector grows at the same level as national level employment in that sector. More formally, developing Overman and Faggio (2014: 96) our instrument is calculated as:

$$\frac{Tech_{s,c}}{Emp_{s,c}} \times \frac{Tech_{t,n} - Tech_{s,n}}{Tech_{s,n}} \qquad (2)$$

where s is 2009 and t is 2015, for TTWA 'c' or Great Britain 'n'. $Tech_{s,c}/Emp_{s,c}$ is the share of local employment in either digital economy or tech in 2009, and we multiply it by the growth rate of either tech or digital economy in Britain overall. Following Faggio and Overman (2014) and Van Dijk (2015) national growth rates are calculated to

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[7] Note that using the Faggio and Overman (2014) method, which uses contribution to total employment growth as the dependent variable, leads to little change in the main results.

[8] Another option would have been to run a year-on-year panel model. Our approach offers two benefits: it allows us to compare our results with other studies of multipliers, such as the Faggio and Overman (2014) paper, and – because the full effect of a new tech job is likely to take some time to come through – it allows us to identify medium term effects.
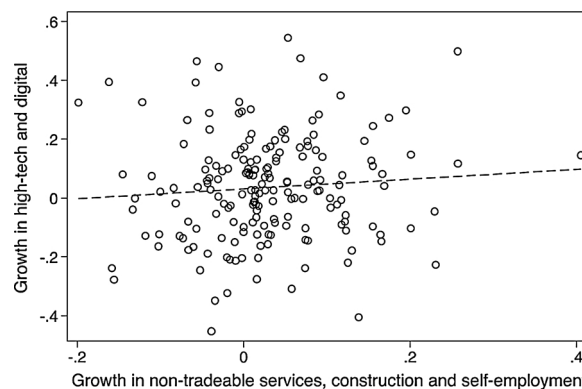
[9] We use growth in digital economy *overall* as the instrument rather than that in each 4 digit-SIC code *within* digital economy or high-technology. This is because our definitions of tech include lots of smaller sub-sectors with lots of zeros in 2009, but also because the sector is relatively finely defined.

Table 1
Summary statistics.

Variable	Source	N	Mean	SD	Min	Max
All high-tech, 2009–2015	BRES	182	0.028	0.087	−0.199	0.405
Digital sector growth, 2009–2015	BRES	182	−0.016	0.281	−0.964	0.965
High-technology growth, 2009–2015	BRES	182	0.056	0.253	−0.696	1.026
Non-tradeable growth, 2009–2015	BRES + APS	182	0.020	0.070	−0.179	0.314
Real low skilled hourly pay growth, 2009–2015	APS	182	−0.045	0.097	−0.319	0.269
Real mid-skilled hourly pay growth, 2009–2015	APS	182	0.026	0.107	−0.333	0.399
Real low skilled hourly pay growth – adjusted for local residential prices, 2009-2015	APS	160	−0.053	0.099	−0.321	0.271
Real mid-skilled hourly pay growth - adjusted for local residential prices, 2009–2015	APS	160	0.033	0.107	−0.311	0.408
High skill %, 2009	APS	182	0.259	0.063	0.069	0.458
Unemployment %, 2009	APS	182	0.068	0.025	0.000	0.148
Total employment (natural log), 2009	BRES + APS	182	11.447	0.950	9.267	15.421

Note: BRES = Business Register and Employment Survey; APS = Annual Population Survey. Regional dummies for East Midlands (15 TTWAs), East (19), North East (9), North West (17), Scotland (22), South East (25), South West (31), Wales (13), West Midlands (14), and Yorkshire and The Humber (17).

exclude employment growth in the TTWA in question.

The instrument helps in that it strips out any of the idiosyncratic shocks which may bias the coefficient. To see this intuitively, consider a case of two TTWAs, one of which has a higher initial share of high tech and digital economy jobs but, because of this, lower employment in non-tradeables. If government policy attempts to simulate high-tech employment in the TTWA with more tech jobs, but in doing so increases non-tradeable employment, it will bias upward the coefficient. But by using an instrument based on predicted shares, these idiosyncratic policy shocks will be stripped out of the model. Using this shift share instrument thus helps move us closer to a causal interpretation.

However, while the shift-share is relatively standard in the literature, it has recently been criticised by Jaeger et al. (2018) in circumstances where there may be correlation in levels over time. This is clearly a problem in the case of high-tech or digital economy employment, as certain TTWAs may have institutions or characteristics which make them more likely to develop this sector. To address the problems of shift-share instruments we draw on a similar argument to Kemeny and Osman (2018), who argue that historic patents will have led to current specialization in high-technology industries, but will not directly influence non-tradeable employment. We use the location of the Schools of Art and Design of the Victorian and Edwardian period of British history (1837–1914). The Victorian period of British history saw a desire to celebrate science and technology alongside a concern that the UK needed to maintain skills in the arts and new technologies such as porcelain. A large number of Schools of Art (originally often called Schools of Design) were established, some by private benefactors but most by the Government's Science and Art Department (Jarrell, 1996). In our case, we argue that the Victorian Art Schools are likely to have an impact on employment and wages for low skilled workers only through their impact on the sectoral composition of the skilled economy. Places with these schools are likely to be focused on technical knowledge which still influences high-technology industries today, and in the period of growth after the crisis they will have seen greater increases in high-tech and digital economy jobs. Yet this impact is specific enough that it impacts through its impact on non-tradeable employment via high-technology employment rather than human capital in general (their presence is only weakly correlated with the share of degree educated workers in 2009, r = 0.16).

We were unable to find a single comprehensive list of these schools. We use the Times Good University Guide 2019 (Times Higher Education, 2019), which lists all arts courses in the UK, as our sampling frame. We then individually research each of these art departments to find their historic roots. We exclude any institution founded after World War One, so exclude top-ranked art departments such as Brunel University (founded in 1966) and the Lancaster Institute for the Contemporary Arts (part of Lancaster University and founded in 2005). The full list then includes some which are located in London (for example, Camberwell College of Arts) but others are located in both ex-

industrial areas (Wolverhampton's Municipal School of Art) and peripheral rural areas (Falmouth College of Art). The resulting instrument should capture the historic roots of technological knowledge, and address the problem that our shift-share IV is based on relatively recent data. However, it does have limitations. In particular, it cannot distinguish between the two sub-sectors. Because of this, we use it to supplement our shift-share instrument in certain models only. A full list of art schools is included in Appendix A3 and a correlation table in A4.

4.3. Jobs multiplier model

The first set of results show the impact of high-technology on jobs in non-tradeable employment and self-employment. The results are given in Table 2. The first three columns present the overall impact using the OLS estimator. The first two include only region dummies (column 1) and then also controls (column 2). While the coefficient is positive and relatively large in magnitude, it is only statistically significant at the 10% level without controls. Following Moretti (2010) we consider the size of the multipliers by multiplying the elasticity against the relative size of the two sectors. However, we do so with caution, given the low statistical significance and so imprecision in the results. These are around 0.4 new jobs per tech job, a relatively low figure compared to US estimates, perhaps accounting for the low level of statistical significance. A visual inspection and Grubb test show a repeated outlier – Darlington, where a large Hitachi plant had opened in 2015. To test if the results stand without this, column 3 repeats the results excluding the outlier. There is little change in the size of the coefficient.

However, in contrast to the OLS results the more robust instrumental variable (IV) results show a positive and statistically significant result between overall high-tech and non-tradeable jobs, with multipliers which are much larger. Columns 4 and 5 show the shift-share IV results with and without controls. The instrument works well, and first stage tests show no cause for concern. The coefficient is larger, and the multiplier increases to between 0.58 and 0.71. The coefficient is higher than that for the OLS, suggesting that endogeneity may bias down the results. Our preferred model is given in column 6 which includes controls but excludes Darlington. This gives a multiplier of 0.71, implying that for every 10 new jobs in digital or high-tech, around 7 new jobs are created in non-tradeables.

Columns 7 to 9 repeat these results with the alternative instrument, the historic art and design schools. The F-statistic is lower but above acceptable levels, and first stage test results are good. The variable for high-technology and digital economy growth is statistically significant in all three cases, suggesting a causal impact on non-tradeable employment. The size of the effect is much higher, however, ranging between 1.79 and 2.06. Given that the results from the shift-share seem more precisely estimated, we interpret this figure as an upper bound on the results.

Our preferred (IV) specification gives a multiplier of just under 0.7

Table 2
Impact of high-technology industries on non-tradeables, 2009-2015.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	$\triangle$Non-tradeable jobs + self-employment, 2009-2015								
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sample	Full	Full	No Outlier	Full	Full	No Outlier	Full	Full	No Outlier
Growth in high-tech and digital, 2009-15	0.0754*	0.0655	0.0687	0.110**	0.101*	0.124**	0.358***	0.320**	0.312**
	(0.0435)	(0.0431)	(0.0434)	(0.0561)	(0.0547)	(0.0525)	(0.129)	(0.162)	(0.159)
High skill %, 2009		−0.0487	−0.0257		−0.0596	−0.0423		−0.127	−0.0987
		(0.141)	(0.140)		(0.133)	(0.131)		(0.142)	(0.138)
Unemployment %, 2009		−0.417	−0.391		−0.385	−0.342		−0.190	−0.173
		(0.340)	(0.329)		(0.326)	(0.317)		(0.359)	(0.355)
Total employment (ln), 2009		0.0102	0.00923		0.00961	0.00823		0.00575	0.00486
		(0.00698)	(0.00697)		(0.00688)	(0.00687)		(0.00905)	(0.00893)
Constant	0.0180	−0.0588	−0.0547	0.0112	−0.0584	−0.0539	−0.0378	−0.0554	−0.0511
	(0.0264)	(0.0790)	(0.0777)	(0.0270)	(0.0754)	(0.0739)	(0.0418)	(0.0809)	(0.0791)
Multiplier	0.43	–	–	0.63	0.58	0.71	2.06	1.84	1.79
First stage results									
Bartik Shift-Share				0.745***	0.734***	0.753***			
				(0.0710)	(0.0724)	(0.0738)			
							0.0311***	0.0314***	0.0314***
Pre-WW1 Schools of Art & Design							(0.00712)	(0.00883)	(0.00885)
R-squared	0.156	0.170	0.171						
Kleibergen-Paap Wald F statistic				110.2	102.9	104.2	18.92	12.64	12.66
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	182	182	181	182	182	181	182	182	181

Note: Robust standard errors reported in parentheses. Columns 3, 6, and 9 exclude Darlington, an outlier. Dependent variable: growth in employment in non-tradeable employment and self-employment, 2009–2015. *$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

non-tradeable jobs created for each new high-tech job (column 6). This figure is substantially below that of Moretti (4–5 jobs) but plausible and consistent with other European evidence. It is close to Moretti and Thulin's (2013) estimated multiplier of around 1.1 for high-tech manufacturing in Sweden. In comparison, in the most similar UK study Faggio and Overman (2014) estimate that each public-sector job creates 0.5 non-tradeable jobs in a local economy, while crowding out 0.4 tradeable manufacturing jobs over the period 2004 – 2007. But this was a period with a much tighter labour market than the period we study.

There are at several reasons why tech jobs in the UK might have a lower multiplier than in US work. Firstly, we use a relatively narrower definition of non-tradeables than other studies. Secondly, British local economies are also 'leaky buckets' compared to US metropolitan areas (Gordon, 1999), in that jobs are more likely to be taken by those in neighbouring TTWAs. Similarly, higher rates of migration in the US may make the response felt in migration; local growth in the UK may be capitalised into local land values. Moreover, the results cover a period of significant labour market weakness in the UK. While employment remained relatively high, there was still clearly some excess slack in the labour market after the financial crisis of 2008 and subsequent recession. A final factor might be that the state has a bigger presence in British society than the United States, and so multiplier employment in sectors such as healthcare might be less responsive than the US case. Our results are similar to Moretti and Thulin's (2013) work on Sweden, although we need to be cautious with the comparison as their definition is focused on manufacturing and a period of stronger economic growth.[10]

We next consider the extent to which the effect comes from the different parts of our high-technology definition, digital economy or high-technology more generally. Table 3 considers the full results, as

Table 3
Disaggregated impact of high-technology and digital economy on non-tradeables, 2009-2015.

	(1)	(2)
Dependent variable	$\triangle$Non-tradeable jobs + self-employment, 2009-2015	
Estimator	2SLS	2SLS
Sample	No Outlier	No Outlier
Growth in digital economy, 2009-15	0.0535*	
	(0.0304)	
Growth in high-tech, 2009-15		0.0967***
		(0.0349)
Constant	−0.0388	−0.0724
	(0.0777)	(0.0764)
Multiplier	0.57	1.21
First stage results		
Bartik Shift-Share	0.838***	0.793***
	(0.0476)	(0.0438)
Kleibergen-Paap Wald F statistic	310.3	328.3
Region dummies	Yes	Yes
Controls	Yes	Yes
Observations	181	181

Note: Robust standard errors reported in parentheses. All models exclude Darlington, an outlier. Dependent variable: growth in employment in non-tradeable employment and self-employment. IV = shift share based on 2009 local industry shares and national growth rate. *$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

given in column 6 of the previous table, for the two separate sub-sectors. The results are weaker for digital economy growth than high-tech, with the coefficient only statistically significant at the 10% level. This shows in the scale of the multipliers: each 10 digital economy jobs create 6 jobs in non-tradeables, but each 10 high-technology jobs create 12. In short, there seems to be significant variation within the high-technology sector.[11]

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[10] One possibility is that high-tech squeezes out other, tradeable industries in the local economy. We do run some tests to see if this occurs, repeating regression 6 in Table 2. We find a positive effect, with a coefficient which suggests a multiplier of around 2 extra tradeable jobs and self-employment created for each 10 high-tech jobs (compared to 8 non-tradeable jobs). However, unsurprisingly given small effect, this is not statistically significant. The direct effect of tech on non-tradeables is stronger than the impact on the tradeable sector.

[11] When including both variables in a simple OLS regression only the classic 'tech' measure is statistically significant.

5. High-technology industries and wages

5.1. High-technology and wages

The external effects of high-technology industries on job creation may also be reflected in wages. The most likely effect is that new jobs increase labour demand and the tighter labour market feeds through into higher wages for the relatively less well-paid. However, this may be traded off against three mechanisms which may reduce wages: (1) the benefits may be capitalised into housing costs, (2) there may be compositional change in the labour market as less skilled workers may shift into non-tradeables from relatively better paid sectors, and (3) new entrants to the labour market may enter at relatively low pay, reducing average wages (although as employment increases this may still be beneficial). To test these effects, we use hourly pay data from the Annual Population Survey (APS). We exclude workers in high-technology to ensure we capture external effects, rather than a mechanical correlation. Regressions are run with the same controls as Table 2 and results are given in Table 5.

We use two measures of wages. The first is simple growth in hourly pay for each skill group, adjusted for inflation.[12] To avoid outliers, we windsorise at the 5th and 95th percentiles. The second is growth in hourly pay, adjusted for inflation using a new indicator which accounts for increases in local housing costs. One significant concern in the literature is that growth may bid up land costs, increasing rental values and so reducing real wages for some. This idea is central to the discussion of high-tech growth in the Bay Area (Walker, 2018), but also important in general equilibrium models of local labour markets (Moretti, 2011).

There are several potential approaches to adjusting for housing costs. US studies, such as Kemeny and Osman (2018), adjust wage data with local median rents, to produce an indicator of local real wages. We adapt Kemeny and Osman's method for the UK case. Unfortunately, there is no official source of rental price data in the UK (the government only publishes data for social housing). Instead, we use the price of residential floorspace. This comes from UK government data taken from Energy Performance Certificates (EPCs) which is then cross-referenced against prices paid from the Land Registry, a UK government department responsible for registering property. We choose to focus on floorspace to account, in part, for differences in type of housing in different local areas. The result is an indicator of price per square metre for housing in each TTWA, which we assume is highly correlated to rents. We then adjust the official UK measure of inflation so it consists of both (1) inflation in consumer prices, which do not vary locally, and (2) housing costs, which vary according to the TTWA. Note that this data is not, unfortunately, available for Scotland so we limit our results using it to England and Wales. Table 4 gives the results of the highest and lowest local inflation data. There is a relatively familiar North-South pattern in property prices over this period. Local housing adjusted price levels increased fastest in London, Slough and Heathrow, Reading, Guildford and Aldershot, and Luton (all TTWAs close to London). Prices increased more slowly in Sunderland, Darlington, Swansea, Hartlepool, and Durham and Bishop Auckland, all relatively lower income TTWAs in the North or Wales.

We estimate two related types of model. We repeat the models we estimate for jobs in Tables 2 and 3 (and given in Eq. 1), which use the first-difference over the period 2009–2015. These models are the helpful for our jobs models as it is not clear from theory whether the impact of tech on local economies will be felt immediately or several years later. They also avoid the noise used in year-on-year data, and provide results which are comparable with the existing literature (e.g.

Table 4
Annual inflation rate, 2009–2015, adjusted for local house price levels.

Rank	TTWA	Inflation	Rank	TTWA	Inflation
1	London	3.33	151	Burnley	2.23
2	Slough and Heathrow	3.16	152	Merthyr Tydfil	2.23
3	Reading	3.08	153	Middlesbrough and Stockton	2.23
4	Guildford and Aldershot	3.07	154	Haverfordwest and Milford Haven	2.22
5	Luton	3.06	155	Blackpool	2.19
6	Brighton	3.03	156	Sunderland	2.17
7	Cambridge	3.03	157	Darlington	2.17
8	Worthing	2.99	158	Swansea	2.17
9	Crawley	2.97	159	Hartlepool	2.15
10	Stevenage and Welwyn Garden City	2.97	160	Durham and Bishop Auckland	2.06

Table presents average annual inflation rate, adjusted for housing costs, between 2009–2015. Data on housing costs comes from EPC data and land registry, provided by UK government. Data on RPI inflation calculations come from Office for National Statistics (2018).

Faggio and Overman, 2014). However, they are less justifiable for models focused on wages. To address this problem, we also estimate a second model using the year-on-year panel data and a fixed effects specification. The fixed effects will help control for city-specific factors which are not included in our model but which may influence growth in high-tech employment. This model is based on Eq. (3) below:

$$ln(HourlyPay_{c\ t}) = \alpha + \beta_1 Tech_{c,t} + \gamma\ X_{c,t} + \varphi_c + \delta_t + \varepsilon \qquad (3)$$

where $ln(HourlyPay)$ is the log hourly pay for either low or mid-skilled workers in travel to work area 'c' in time 't', using a localised inflation measure which accounts for local house price changes. *Tech* is the log of total employment in digital and high-technology industries, the vector *X* is a set of time-variant city-specific controls for total TTWA employment (log), the share of skilled workers in our top educational category, and the unemployment rate. φ is a set of TTWA specific fixed effects which should capture time invariant factors which are likely to influence wages, δ is a set of year fixed effects intended to control for changes in the national economy. The error term is ε.

This specification should control for TTWA-specific time invariant factors which may influence both the low skilled labour market and growth in high-technology, and so address these concerns. We use the shift-share instrument as this is time-variant and so can account for the causality challenges considered above.

The results are given in Table 5. Overall, these show that high-tech growth increases average wages for mid-skilled workers, but reduces average wages for low skilled workers. Columns 1–2 and 3–4 give results for low skilled workers, using first the change over the period and then the fixed effects models and using both RPI inflation and our measure with local housing costs. All four models show a negative and statistically significant effect from high-tech on wages for workers in the bottom third of educational attainment. The effect is only slightly larger in columns 2 and 4 which account for increases in local housing costs, showing that wages are even further eroded once we account for increased costs.[13]

Of course, the effect of this erosion would be worst for some groups (the young, who would be more reliant on the rental market) and may actually reflect a gain to homeowners. They are similar to the findings of Kemeny and Osman (2018) who study the United States and find

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[12] We use Retail Price Index "J" as the best living standards deflator as it includes a broader measure of housing costs than other indicators, including Council Tax, mortgage interest payments, depreciation and estate agent's fees.

[13] One plausible argument here is that the negative effects of price inflation for some workers are outweighed by a positive effect of stronger demand for work in construction, a key non-tradeable sector. We are grateful to a referee for this point.

Table 5
Impact of high-technology industries on low and mid-skilled hourly pay, 2009-2015.

Dependent variable	(1) Low-skilled wages	(2)	(3)	(4)	(5) Growth in medium-skilled wages, 2009-2015	(6)	(7)	(8)
Estimator	2SLS △ 2009-2015	2SLS △ 2009-2015	2SLS Annual Panel	2SLS Annual Panel	2SLS △ 2009-2015	2SLS △ 2009-2015	2SLS Annual Panel	2SLS Annual Panel
Inflation measure	RPI	RPI with local housing costs	RPI	RPI with local housing costs	RPI	RPI with local housing costs	Annual Panel	Annual Panel
High-tech and digital emp.	−0.166**	−0.185**	−0.0814**	−0.0927**	0.205***	0.210***	0.295**	0.284**
	(0.0744)	(0.0825)	(0.0360)	(0.0375)	(0.0718)	(0.0809)	(0.120)	(0.120)
High-skilled workers (%)	0.403***	0.360**	0.211***	0.160***	−0.350*	−0.433**	0.0123	−0.0384
	(0.153)	(0.165)	(0.0222)	(0.0228)	(0.194)	(0.209)	(0.147)	(0.147)
Unemployment rate (%)	−0.00382	0.165	−0.160*	−0.158*	−0.267	−0.153	0.0497	0.0472
	(0.321)	(0.379)	(0.0896)	(0.0864)	(0.375)	(0.454)	(0.259)	(0.250)
Total employment (log)	−0.00711	−0.0113	0.121	0.0418	−0.00291	−0.00773	0.0154	−0.0639
	(0.00714)	(0.00829)	(0.0965)	(0.0668)	(0.00813)	(0.00976)	(0.118)	(0.147)
Constant	−0.0213	0.0284	1.481	−2.114**	0.133	0.197*	−0.398	−3.993*
	(0.0907)	(0.101)	(1.297)	(0.895)	(0.0988)	(0.112)	(1.714)	(2.126)
First stage results								
Bartik Shift-Share	0.734***	0.703***	0.336***	0.336***	0.734***	0.703***	0.336***	0.336***
	(0.0724)	(0. 0942)	(0.0542)	(0.0542)	(0.0724)	(0.0942)	(0.0542)	(0.0542)
R-squared								
Kleibergen-Paap Wald F statistic	102.9	86.4	38.5	38.5	102.9	86.4	38.5	38.5
Region dummies	Yes	Yes			Yes	Yes		
TTWA Fixed effects			Yes	Yes			Yes	Yes
Year Fixed effects			Yes	Yes			Yes	Yes
Observations	182	160	1,120	1,120	182	160	1,120	1,120
Number of TTWA			160	160			160	160

Note: Standard errors reported in parentheses, clustered on region in FE models. Dependent variable: growth in hourly pay for low skilled (columns 1–4) or medium-skilled (columns 5–8) not working in high-tech. IV = shift share based on 2009 local industry shares and national growth rate. Controls are initial year values for columns 1, 2, 5 and 6, city/year values for models estimated with fixed effects.
*p < 0.1. **p < 0.05. ***p < 0.01.

relatively little difference between nominal and real (after accounting for housing costs) wage growth. They conclude that the "the interactions in iconic tech hubs between tech and strongly inelastic housing markets is not the universal, or even majority urban tech experience" (pp. 1737). Our result probably has a similar explanation as, despite strong house price increases in London and nearby TTWAs, prices increased by less elsewhere. In contrast to the reduced hourly pay for low-skilled workers, the growth of high-tech industries seems to have a positive impact on medium-skilled hourly pay. The coefficient is only slightly larger when including local house price changes in the measure of inflation.

We consider mid-skilled wages in columns 5–8. In contrast to the negative results for low-skilled average wages, we find a positive effect for mid-skilled workers, even when controlling for housing costs. This result is similar to that of Lee and Rodríguez-Pose (2016) for US cities: growth in high-technology is associated with gains for middle-earners, but does not seem to be associated with increased wages for workers on low incomes. While there are real benefits from high-tech growth for mid-skilled workers, the benefits for low-skilled workers are more ambiguous.

5.2. Mechanisms

The results presented above have both positive and negative interpretations: high-tech growth seems to increase the number of jobs, but reduce wage growth. What might be driving this? There are two obvious channels. The first is a *worker composition* effect. If growth in high-tech sectors increases the number of jobs, the tighter labour market could allow 'marginal' workers to enter – these workers would have lower productivity than those already in employment, and so would reduce the average wage. If this was true, new jobs would be created for low skilled workers, but the jobs would be in non-tradeables. Overall, this would probably be a net gain for low skilled workers as more would be employed. A second explanation is the *sector composition* effect, if high-tech industries change the structure of the low skilled labour

market, for example in leading to a shift from manufacturing to personal services. This would result in a decline in low-skilled tradeable employment. This may indicate a net loss for low skilled workers, who would be shifting to less well-paid employment.

To test these two mechanisms, we run the same regressions as Table 2 (Eq. 1) but with four alternative variables: (1) low-skill non-tradeable employment, (2) mid-skill non-tradeable employment, (3) low-skill tradeable employment, and (4) mid-skill tradeable employment. These are calculated by first estimating total employment and self-employment using the BRES numbers with a self-employment estimate from the APS. We then estimate the share of total employment and self-employment by each skill group and tradeable category (again, excluding high-tech employment), and then use this to come to an estimate of total jobs. The results are given in Table 6, which focuses on the 2SLS results.

The first two columns show the impact of high-tech on non-tradeable employment by skill group; columns three and four show the impact on tradeable employment. If negative wage growth is driven by a worker composition effect, with new entrants coming into the labour market, we would expect a positive result for non-tradeables. If driven by a sector compositional shift away from tradeable industries, for example if well paid manufacturing employment was squeezed out, this would be expressed in a negative result for low paid employment. The results suggest that for low-skilled workers, it is a worker compositional effect which seems to apply here. High-tech industries seem to increase low skilled non-tradeable employment, but have no impact on low skilled tradeables. In contrast, increased wage growth in the medium skill labour market seem to be driven simply by labour market tightness – there is no clear impact on whether jobs are tradeable or non-tradeable. This is because the lion's share of new jobs go to low-skilled workers: the 2SLS delivers a multiplier of around 0.6, close to the estimated multiplier for all workers of 0.7 for high-technology overall. In short, for each 10 new high-technology jobs employment increases by 7 in non-tradeables, of which 6 go to low-skilled workers.[14]

Two other statistics show that wages are lower for non-tradeables,

Table 6
Impact of advanced sectors on low-skill employment, 2009–15.

	(1)	(2)	(3)	(4)
Dependent variable:	Low-skilled Non-tradeable	Mid-skilled Non-tradeable	Low-skilled Tradeable	Mid-skilled Tradeable
Estimator:	2SLS	2SLS	2SLS	2SLS
Growth in high-tech and digital, 2009-2015	0.427** (0.187)	0.164 (0.177)	−0.0150 (0.175)	−0.0363 (0.215)
High-skilled workers (%), 2009	−0.0990 (0.480)	0.245 (0.483)	1.357*** (0.417)	0.762** (0.385)
Unemployment rate (%), 2009	1.183 (1.197)	0.139 (1.098)	1.049 (0.989)	1.781 (1.248)
Total employment (ln), 2009	−0.0288 (0.0265)	0.0773*** (0.0268)	−0.0558*** (0.0207)	−0.0243 (0.0229)
Constant	0.351 (0.307)	−1.189*** (0.307)	0.448* (0.251)	0.0202 (0.305)
Multiplier	0.58	–	–	–
First stage results				
Bartik Shift-Share	0.734*** (.0724)	0.734*** (.0724)	0.734*** (.0724)	0.734*** (.0724)
Kleibergen-Paap Wald F statistic	102.9	102.9	102.9	102.9
Region dummies	Yes	Yes	Yes	Yes
Observations	182	182	182	182

All models estimated using 2SLS. IV = shift share based on 2009 local industry shares and national growth rate.
Dependent variable: employment and self-employment by skill group / tradeable group (excluding high-technology). Robust standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

providing support for the idea that low skilled non-tradeable employment growth would reduce wage growth. A simple correlation between change in real hourly pay between 2009–2015 has a −0.23 correlation with change in non-traded low skilled jobs (p < 0.01). The relationship between wages and traded low-skilled jobs is positive (0.10) but not statistically significant (p = 0.1739). Second, wages are higher in tradeables than non-tradeables. In 2015 the average hourly pay for low-skilled workers in a tradable industry was around £0.86 higher than those in non-tradeables (p < 0.01). There seems to be little relationship between tradeables and high-technology, suggesting that there was no 'crowding out' of other industries in this period. This is perhaps unsurprising given the slack in the economy in 2009.

Overall, high-technology industries seem to have a positive impact on jobs. While there is a positive coefficient on mid-skilled employment, most new jobs seem to be for low-skilled workers in non-tradeable sector. This is consistent with a view that growth in high-tech leads to new, non-tradeable jobs in personal services. Most of these jobs go to low-skilled workers, but are poorly paid, reducing average wages, although this is still a net gain to low-skilled workers.

6. Conclusions

Innovative, high-tech industries are an important component of many economic development strategies. One important justification for these strategies is that there will be benefits to low-skilled residents. Yet there is relatively little evidence on this point. This paper has presented new evidence on the impact of high-tech sectors on job creation and wages for low-and mid-skilled workers in British local labour markets. It has three central findings. First, there is a significant multiplier from high-tech, with each new job creating around 0.7 non-tradeable jobs. This finding provides an apparently strong justification for strategies seeking to attract and grow the high-technology sector. However, there have been many failed attempts to do so (Lerner, 2009).

Our second finding is that high-tech growth lowers the average wage of local low skilled workers, particularly when controlling for increased house prices. Low-skilled tradeable employment does not fall, so these reduced wages are caused by new entrants to the labour market, not existing workers earning less. Employment rates for low skilled workers vary spatially much more than those for mid or high-skilled workers, whose labour market participation tends to be high wherever they live (Green and Owen, 2006). In contrast, low skilled workers are both more reliant on the strength of local labour demand and more likely to be employed in non-tradeables. So while this result is negative in some senses, it still indicates increased welfare for low skilled workers: if existing workers remain in employment, presumably at the same wages as before, but the previously unemployed enter the labour market then there will be a net benefit both to the economy overall and to the previously unemployed worker. But it suggests that new jobs are not high-quality. Policy may wish to combine a focus on growing high-tech industry with one on upgrading jobs in the non-tradeable sector.

A third result is that there are benefits to mid-skilled workers. This finding may seem controversial when compared to the literature on job polarisation which has tended to stress the decline of mid-skilled jobs (see Autor and Dorn, 2013, for US evidence, or Salvatori, 2018 for UK evidence). Our results differ slightly as they are for skill groups, rather than the occupational groups which are the focus of most employment polarisation research. But they show a more positive story, we suspect because they reveal the importance of spill-overs into the mid-skilled labour market which are normally the focus of research on low skilled workers (Mazzolari and Ragusa, 2013).

Our findings present a challenge for economic development policy. Policymakers aiming to improve living standards for low skilled workers face two basic options. The classic method of economic development is to stimulate local demand and, in doing so, raise the employment rates of low skilled workers. Attracting high-technology sectors may be one good way to do this, but it needs to be accompanied with efforts to try to upgrade skills or increase productivity. Alternatively, policy could focus on ensuring low skilled workers are in employment in tradeable sectors, such a manufacturing, which might create good jobs in the first place. Yet global competition and new technology have made these sectors hard to sustain. Clearly, economic development is more complex than the simple model presented here. It is important to note, of course, that creating jobs for low skilled workers is only one goal of policy focused on high-tech industries. There might be other benefits, such as improved production processes in other sectors or the general benefits of technological change.

An important caveat to this study is the time period we focus on. This was an unusual time for the UK economy, comprising relatively strong employment performance but also very weak productivity. Much of the new employment was non-standard (Green and Livanos, 2017). An important avenue for future work would be to see if the results hold over different time periods. Given weak wage growth after the crisis, our wage results will have been biased downwards because of the slack in the market. Workers may first take employment, if available, with wages increasing only once workers had sufficient bargaining power (or the ability to move from less well paid to better paid jobs). Moreover, while we divide employment up by skills, we do not consider other potential inequalities. Echeverri-Carroll et al. (2018) show complicated patterns of gains and losses according to gender and skill-group. The non-tradeable jobs we consider in this paper have a gender bias, and future work may wish to investigate this further. Finally, while our data allows us to consider the effect of two definitions of the high-technology sector, future studies may wish to disaggregate these broad definitions further.

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[14] Tests also show new jobs go British born workers, rather than non-British workers.

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