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Who gains from high-tech growth? High-technology multipliers, employment and wages in Britain

Neil Lee[1] & Stephen Clarke[2]

Abstract

Do residents 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 this question. 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 traditional 'high-tech' or the digital economy – have a positive jobs multiplier, with each high-tech job creating around 0.9 local non-tradeable service jobs, around 0.6 of which go to low-skilled residents. Employment rates for mid-skilled workers do not increase, but they benefit from higher wages. Yet the benefits for low-skilled workers come with a catch: they gain from increased employment rates, but lose as new jobs are poorly paid service work so lower average wages.

Keywords: Living standards; Wages; Multipliers; High-technology; Cities; Inequality

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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 & Shapira, 2008; Brown & 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 or medium-skilled workers? The literature on this question essentially takes two positions (Lee & Rodríguez-Pose, 2016). Most studies have taken an optimistic view, based on the idea that high-technology is a tradeable sector which would – through a 'multiplier effect' – create jobs in other sectors of the 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.

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 residents (Bartik, 1991; Goetz et al., 2011; Breau et al., 2014). Studies of cities with strong high-tech economies have highlighted the problems of inequality and polarization 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). While growth in high-tech may create new jobs, these jobs are not all well-paid. Instead, growth may create new low-paid personal service jobs while simultaneously squeezing out employment in relatively well-paid tradeables.

A number of studies now consider the impact of high-technology on local labour markets. The 'multipliers' literature tends to find that high-technology, tradeable industries have a positive net jobs multiplier, although there is disagreement about the size of the gains (Moretti, 2010; Moretti & Thulin, 2013; Van Dijk, 2016). However, empirical work on wages tends to be rather more pessimistic and highlight problems of inequality. For example, Echeverri-Carroll and Ayala (2009) find a wage premium for workers in innovative US cities, but that the premium is larger for skilled than unskilled workers. Breau et al. (2014) show innovation increases inequality in Canadian cities. Lee and Rodríguez-Pose (2016) show tech-sector growth in US metropolitan areas increases wages for middle-income earners, but does not reduce poverty. In short, these studies find a nuanced picture of gains for some in high-tech local economies, but not the most disadvantaged.

The literature on high-tech industries and local labour markets has a number of limitations, however. Firstly, studies often use very broad indicators of high-technology industries. For example, Moretti's (2010) seminal study (which, to be fair, did not explicitly focus on tech), defines high-technology as three sectors - Machinery and Computing Equipment, Electrical Machinery and Professional Equipment - which are removed from most common definitions of tech (it would not, for instance, include Google). This is unhelpful for policymakers who need more precise targets. Second, 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). Fourthly, studies tend to focus on either job creation (e.g. Moretti & Thulin, 2013) or wages (e.g. Lee & Rodríguez-Pose, 2016) with little work testing both. These omissions are particularly important for innovation studies, given both the importance of spatially targeted investments in high-technology as an innovation policy tool (Brown & Mason, 2014) and growing interest in how innovation-intensive growth can be made inclusive (see Stilgoe et al. 2013; Zehavia & Breznitz, 2016).

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. It adapts the multiplier models used by Moretti (2010) and tests the impact of two high-technology industries – the "classic" high-technology sector itself and the newer digital economy sector – on both employment and wages for less educated groups. 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. Moreover, we also test for a set of alternative sectors – including the creative industries and tradeable finance – which are often the target of economic development, but find no evidence of similar multipliers. High-technology industries seems to be different to other advanced industries.

The paper is structured as follows. Section 2 sets out the basic framework for analysis in the literature on multipliers, and extends it to develop hypotheses about the impact of different sectors and the living standards of local residents. 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. Job creation, occupational change and living standards

2.1 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 leads to a "multiplier effect" in other parts of the local economy. For example, if a high-tech firm is created in an area, the local economy benefits from the spending of the firm, the workers, and the other industries which gain. The size of the multiplier depends on the extent of local spending, with this varying by sector.

Several factors determine the size of the multipliers from different industries. 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 (Bakshi et al., 2009; Isaksson et al., 2016), and this might happen locally. The second impact comes from the workforce's local spending. Well-paid, high-skilled workers have more money to spend locally than less well-paid workers (Moretti & Thulin, 2013). Some industries, such as the creative workers, may make a local area fashionable, attract other skilled workers (Lee, 2014).

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 employment, occupations and wages

Despite the efforts placed by policymakers on attracting and retaining high-technology industries (Brown & Mason, 2014), there is little evidence on the distribution of the gains (Lee & 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 & Dorn, 2013). Empirical studies of human capital multipliers come to similar conclusions: Kaplanis (2011a; 2011b) 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, 2010). In particular, growth in high-technology industries may raise land costs. Moreover, as the labour market tightens, wage costs will also increase. For non-tradeables, growth in tech will increase demand. But other tradable industries will not benefit in the same way, so tech growth may reduce employment in other sectors. 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., 2017). 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. Numerous studies consider external effects of high-technology industries on other locals. Echeverri-Carroll and Ayala (2009) use a cross-section and IV 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. In a panel study using a shift-share instrument, Lee and Rodríguez-Pose (2016) who 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 residents, but that the benefits accrue to those with incomes around double the poverty line and do not trickle down to those in poverty. Studies on the relationship between innovation and inequality tend to find a positive link, 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 & Rodríguez-Pose, 2013; Breau et al., 2014).

Case study evidence is more equivocal, and 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), a measure of functional labour markets. Developed by Coombes 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).[1] Using these commuting zones should minimize 'leakage' of any multiplier outside the local economy (Gordon, 2002; Gordon & 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 local BRES data is not published.

While the TTWAs are defined using very small geographical units, the data used in this paper is only available for larger Local Authority (LA) units.[3] To address this a new set of TTWAs are constructed which are defined entirely using LA boundaries. Each local authority 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, the boundaries used for London is the entire GLA area. The result is a smaller number of TTWAs with a larger average size, and a significantly reduced number of very small TTWAs.

3.2 Defining high-technology industries

The main source of data for employment is the Business Register and Employment Survey (BRES), the best local-level employment survey in the UK and the official source of employment estimates. Information is collected from businesses across the UK as a whole,

[3] 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.

with around 80,000 firms sampled each year from a population of around 2 million. 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.

A complication is that around 45% of UK employment growth since the 2008 recession has been in self-employment (Tomlinson & Corlett, 2016), much of which was non-tradeable such as driving or construction. 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.

The BRES data allows analysis at a fine sectoral level. Following existing literature, we first divide industries into two types: tradeable and non-tradeables. 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 as untradeable; those which are highly concentrated are tradeable. The non-tradeable industries include 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).

Our definition of high-technology includes two related sub-sectors. First we use *classic high-technology*, an adaptation of that developed by the Bureau of Labour Statistics (BLS) in the United State, and used by Fallah et al. (2014), with the exclusion of digital economy firms. It is sectors with the highest occupational share in science, technology and engineering workers. This includes petroleum refinement, elements of Manufacture of irradiation, electromedical and electrotherapeutic equipment, Research and Development, manufacture of elements.

Traditional high-tech definitions do not capture leading edge, high-technology firms (Nathan & Rosso, 2015). We also use a *digital economy* definition, according to the UK government

[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.

definition (Department of Culture, Media & Sport, 2016) to include industries such as Manufacture of electronic components and boards, software, telecommunications, computer programming. Full sectoral definitions are in Appendix A. Together we refer to these as *overall high-technology*.

The analysis is focused on the aggregation of these two industries. On average, just under 7 percent of employment in British cities is in these sectors, a figure which is constant between the two periods. Figure 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 advanced sectors and growth in non-tradeables and self-employment.

Insert figure 1 around here

3.3 Wages and employment

The data for wages and employment rates comes from the Annual Population Survey (APS), a rolling quarterly labour market survey (Office for National Statistics, 2017). The APS data is an individual survey focused on 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 allow 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.

The focus of this paper is on benefits to low and mid-skilled workers. 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 has expanded, while the average quality has fallen). To account for this, we divide all those aged 18-64 into three 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 GCSE education (essentially these are people who stayed on at school after their first formal qualification); and, low skilled workers with 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 the sectors from indicators using these skill groups.

4. Model and results

4.1 Empirical strategy

To estimate the impact of tradeable sectors on non-tradeable employment in the same city, we follow Moretti (2010) and estimate adapted models of the form:

$$\triangle NonTrade_c = \alpha + \beta \triangle Tradeable_c + \varepsilon_c \qquad (1)$$

Where, $\triangle NonTrade_{ct}$ is the change in the log number of non-tradeable jobs and self-employment in city c, $\triangle$ Tradeable$_c$ is the change in the log number of tradeable jobs in city c, ε is the error term. The key figure of interest is the coefficient β on each advanced industry considered. If this is positive, this indicates that growth in the advanced industry is associated with growth in non-tradeables.[5]

We also use the controls from Faggio and Overman's (2014) model to control for initial conditions in 2009. 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 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 area dummies for broad regions: Scotland, North, Wales, the Midlands and the South. These should control for unobserved region-specific factors and differential policy in Wales and Scotland.

The key problem with this model is endogeneity. Some third factor may influence both growth in high-tech and changes in jobs and living standards for the population. If this was the case, omitted variables captured in the error term would be correlated with growth in tech. For example, the presence of a dynamic entrepreneurial culture in a local area may drive growth in employment in high-tech industries, but also be associated with increased labour demand for low

[5] 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.

skilled workers. There is also the potential for reverse causation, with low-income growth being associated with an influx of a particular sector, rather than the sectoral change influence growth.

To address this issue an instrumental variable (IV) approach. Building on Bartik's (1981) seminal paper (and an approach used by Moretti, 2011; Faggio & Overman, 2014; Van Dijk, 2016 and Lee & Rodríguez-Pose, 2016 to investigate multipliers), a shift share instrument is calculated using predicted employment growth based on initial local shares (in 2009) and national growth rates over the subsequent period. Following Van Dijk (2015) this is calculated to exclude employment growth in the TTWA in question, and so avoid direct endogeneity. This should control for endogeneity between jobs growth and local living standards and provide the most robust estimate of the multiplier effects.

4.2 Jobs multiplier model

The first set of results show the impact of advanced sectors on jobs in non-tradeable employment and self-employment. The results are given in table 2. The three columns present the overall impact using the OLS estimator. The first two include only area dummies (column 1) and then also controls (column 2). While the coefficient is positive and relatively large in magnitude, in neither case is it statistically significant. 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 statistical significance which means the estimates are imprecise. These are around 0.4 new jobs per tech job, a relatively low figure compared to US estimates which perhaps accounts for the lack of significance. A visual inspection and Grubb test show an extreme outlier – Darlington – and leverage tests show it influences the results.[6] To test if the results stand without this, column 3 repeats the results excluding the outlier. The result becomes, just, statistically significant but only weakly and there is little change in the size of the coefficient or multiplier.

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 almost double in magnitude. Columns 4 and 5

[6] Further research reveals this to be the opening, in 2015, of a large high-tech Hitachi manufacturing plant in 2015 (construction having finished the year before). This will have led to a massive increase in high-tech employment, but is unlikely to have any impact on local demand and may have reduced construction employment (construction jobs having gone).

show the basic IV results. The instrument works well, and first stage tests show no cause for concern. The coefficient is larger, and the multiplier increases to between 0.87 and 0.95. The coefficient is higher than that for the OLS, suggesting that endogeneity may bias down the results. To see which sub-sector is driving the results, columns 6 and 7 test them individually. Both show a positive result, but the digital effect is larger and statistically significant. Each additional digital job creates almost 1.2 non-tradeable jobs; each ‘classic’ tech job creates around 0.86.

Our preferred (IV) specification gives a multiplier of just under 0.9 non-tradeable jobs created for each new high-tech job (column 5). This figure is substantially below that of Moretti (4-5 jobs) but plausible and consistent with other European evidence. It is very close to Moretti and Thulin’s (2013) estimated multiplier of around 1.1 for high-tech manufacturing in Sweden. 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.

There are at several reasons why tech jobs in the UK might have a lower multiplier than in US work. US estimates tend to use a broader definition of non-tradeables than the more specific definition used here. Moreover, these local economies are – compared to US metropolitan statistics – ‘leaky buckets’ (Gordon, 2002) so jobs which are created may not be local or may be filled by commuters. 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. Finally, 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.

Insert table 3 around here

In addition, we test whether any results for high-technology apply equally to other ‘fashionable’ sectors. We first test two sectors which are common targets of economic development policy: *creative industries* – using the commonly adopted DCMS (2015) definition, this includes fashion, Advertising, Architecture, Crafts, Design, Designer fashion, Video, film and photography, Publishing, and Radio and TV (but excluding software); and, *Tradeable finance* – defined as those parts of finance which do not serve local demand, so are not considered non-tradeable in the Jensen and Kletzer (2006) definition. This includes Fund Management, Insurance Brokers, Pension Funding and other non-local financial services. Creative industries are the subject of a boosterist literature about its economic potential. Tradeable finance, in contrast, is a well-paid sector. Cities such as Edinburgh have tried to develop (and protect) these jobs on the basis of potential job creation.

Table 3 presents these results. We report here the 2SLS results with full controls, but our findings are similar for other specifications. The coefficient is positive in three of the four cases, but not statistically significant. The size of the coefficient is largest for creative industries. One interpretation here is that there is probably a positive impact from this sector, but that it varies according to local context. Given the diversity of the sector, this seems likely. Overall, these results suggest that high-tech industries are to some extent different from other advanced industries in their external impact.

5. High-technology industries and wages

5.1 High-technology and wages

Job creation is an important goal, but so is the impact of high-technology industries on wages for less well-educated workers. To test this, we use a new variable: growth in hourly pay for each skill group over the two periods. Hourly pay is corrected for inflation[7], and windsorised at the 5th and 95th percentiles to avoid outlieros. To capture external effects, rather than a mechanical correlation, workers in high-technology are excluded from this variable. Regressions are run with the same controls as table 2. The results are given in table 4.

Insert table 4 around here

The results show that high-tech growth increases wages for mid-skilled workers, but reduces wages for low skilled workers. Columns 1 – 2 give OLS and IV results for low skilled workers. They show a negative and statistically significant impact on wages for less well-educated workers, regardless of model specification. In contrast, however, the growth of high-tech industries seems to have a positive impact on medium-skilled hourly pay. This result is similar to that of Lee and Rodríguez-Pose (2016) for US cities: growth in advanced sectors is associated with gains for middle-earners, but does not seem to be associated with increased wages for workers on low incomes. However, the result here is more extreme, as it suggests that growth in high-technology industries is associated with lower growth in real hourly pay for these groups.

5.2 Mechanisms

The results presented above are both positive and negative: 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

[7] 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.

enter – these workers would have lower productivity than those already in employment, and so would reduce the average wage. In this was true, new jobs would be created for low skilled workers, but the jobs would be in non-tradeables. A second explanation is the *compositional* 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.

Insert table 5 around here

To test these two mechanisms, we run the same regressions as table 2 but with four alternative variables: (1) low-skill non-tradeable employment, (b) mid-skill non-tradeable employment, (c) low-skill tradeable employment, and (d) mid-skill tradeable. These are calculated by first estimating total employment/self-employment using the BRES numbers with a self-employment estimate from the APS. We then estimate share of total employment/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 4, 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 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. Both OLS and 2SLS results show that high-tech industries seem to grow low skilled 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 delivering a multiplier of around 0.6, close to the estimated multiplier for all workers of 0.9 for high-technology overall.

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

6. Conclusions

Innovative, high-tech industries are an important component of many economic development strategies. There is a presumption that the benefits of these high-end strategies reach those on low incomes, but 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 0.9 non-tradeable jobs. This finding provides an apparently strong justification for strategies seeking to attract and grow the high-technology sector. Yet it is very hard for local areas to develop sectors without some comparative advantage (although this does not stop policymakers trying). Evidence does suggest that some local characteristics, including universities (Fallah et al., 2014) and transport links (Albalete, & Fageda, 2016), may be associated with high-tech growth. Yet it is hard for policymakers to develop new high-tech industries, and there have been many well-documented failed attempts (Lerner, 2009). Moreover, the relatively modest size of the multiplier compared to US evidence suggests caution is needed before large investments are made. The direct impact of any job-creation in high-technology sectors is probably larger than the indirect impact in non-tradeables.

Our second finding suggests a second potential issue with economic development strategies focused on tech. High-tech growth leads to lower average wages for low skilled workers. Low-skilled tradeable employment does not fall, so the reduced wages are caused by new entrants to the labour market, not existing workers moving to less well-paid jobs. Employment is better than unemployment, so this is a net gain. It is felt particularly by low skilled workers for two reasons. They are more reliant on the strength of local labour demand: in the period studied in the UK, employment rates for low skilled workers varied spatially much more than mid or high-skilled workers, which remained high wherever they lived (Green & Owen, 2006). Moreover, low-skilled workers are more likely to be employed in non-tradeables than better skilled workers.

This finding presents 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, so raising the employment rates of low skilled workers. Attracting innovative sectors may be one good way to do this, but it needs to be accompanied with efforts to try and upgrade skills or productivity for these workers. 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 this approach faces challenges as competition makes these sectors hard to sustain. Clearly, economic development is more complex than the simple model presented here. But there is no easy policy option.

There are two important caveats to this study, both of which could be addressed in future work. The first is the time period it covers. This was an unusual period for the UK economy, comprising relatively strong employment performance but also very weak productivity. Much of the new employment was non-standard (Green & Livanos, 2016). An important avenue for future work would be to see if the results hold over different time periods. Second, evidence on cities with strong high-tech economies often highlight the high costs faced by workers (Florida, 2017). For example, Kemeny and Osman (2017) suggest that rises in living costs can offset higher wages in some cities (see also Storper et al., 2015). The challenge here is that we find reductions in average wages, which may – in tandem with increased costs – lead to a more negative picture than that given here. Unfortunately, we can find no feasible way of testing this in the framework we use here. Future work using alternative data could consider how cost of living influences these results.

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Tables and figures

Table 1. Summary statistics

Variable	Source	N	mean	sd	min	max
All high-tech, 2009-2015	BRES	182	-0.118	0.165	-0.714	0.449
Digital sector growth, 2009-2015	BRES	182	0.00316	0.285	-0.964	0.964
High-technology growth, 2009-2015	BRES	182	0.0508	0.245	-0.735	0.841
Creative industries growth, 2009-2015	BRES	182	-0.0679	0.326	-1.844	0.970
Tradeable finance growth, 2009-2015	BRES	182	-0.0846	0.486	-1.767	1.472
Non-tradeable growth, 2009-2015	BRES + APS	182	0.0208	0.0856	-0.206	0.396
Real low skilled hourly pay growth, 2009-2015	APS	182	-0.0441	0.0973	-0.317	0.256
Real mid-skilled hourly pay growth, 2009-2015	APS	182	0.0268	0.106	-0.321	0.401
High skill %, 2009	APS	182	0.279	0.0641	0.103	0.463
Unemployment %, 2009	APS	182	0.0685	0.0247	0	0.148
Total employment (natural log), 2009	BRES + APS	182	11.33	0.979	9.145	15.17

Note: BRES = Business Register and Employment Survey; APS = Annual Population Survey.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	△Non-tradeable jobs + self-employment, 2009-2015						
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
Growth in high-tech and digital, 2009-15	0.0696	0.0603	0.0705*	0.165***	0.151***		
	(0.0429)	(0.0427)	(0.0424)	(0.0538)	(0.0544)		
Growth in digital, 2009-15						0.0940***	
						(0.0352)	
Growth in tech, 2009-15							0.0811*
							(0.0465)
High skill %, 2009		-0.0517	-0.0313		-0.0616	-0.000322	-0.0865
		(0.118)	(0.117)		(0.114)	(0.112)	(0.117)
Unemployment %, 2009		-0.391	-0.340		-0.292	-0.148	-0.487
		(0.320)	(0.315)		(0.325)	(0.301)	(0.315)
Total employment (ln), 2009		0.0143**	0.0126*		0.0130*	0.00811	0.0176***
		(0.00714)	(0.00708)		(0.00728)	(0.00746)	(0.00675)
Constant	0.0324**	-0.0911	-0.0805	0.0251*	-0.0879	-0.0410	-0.121
	(0.0140)	(0.0789)	(0.0784)	(0.0147)	(0.0757)	(0.0775)	(0.0762)
Area dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	182	182	181	182	182	182	182
R-squared	0.067	0.089	0.085				
First stage F test				165.1	166.3	147	200.5
Multiplier	0.40	0.35	0.40	0.95	0.87	1.17	0.86

Note: Standard errors reported in parentheses. Column 3 excludes 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

Table 3. Impact of selected sectors on non-tradeables, 2009-2015

	(1)	(3)	(4)	(5)
Dependent variable	△Non-tradeable jobs + self-employment, 2009-2015			
Estimator	2SLS	2SLS	2SLS	2SLS
Creative industries growth, 2009-2015	0.0166			
	(0.0240)			
Tradeable finance growth, 2009-2015		0.0167		
		(0.0171)		
Manufacturing growth, 2009-2015			0.0246	
			(0.0601)	
Public sector growth, 2009-2015				-0.0694
				(0.103)
Constant	0.00480	-0.0799	-0.0989	-0.103
	(0.0865)	(0.0812)	(0.0836)	(0.0870)
Initial Controls	Yes	Yes	Yes	Yes
Area Dummies	Yes	Yes	Yes	Yes
Observations	182	182	182	182
First stage F test	198.3	256.4	192.9	349.5

Note: Standard errors reported in parentheses. 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

Table 4. Impact of advanced industries on low skilled hourly pay, 2009-2015

	(1)	(2)	(3)	(4)
Dependent variable	Growth in low-skilled wages, 2009-2015		Growth in medium-skilled wages, 2009-2015	
Estimator	OLS	2SLS	OLS	2SLS
Growth in high-tech and digital, 2009-2015				
	-0.112***	-0.180***	0.0988**	0.156**
	(0.0395)	(0.0630)	(0.0448)	(0.0722)
High-skilled workers (%), 2009	0.389***	0.397***	-0.257	-0.263
	(0.136)	(0.132)	(0.192)	(0.187)
Unemployment rate (%), 2009	0.0432	-0.0307	-0.359	-0.296
	(0.315)	(0.317)	(0.381)	(0.369)
Total employment (log), 2009	-0.00913	-0.00815	0.00182	0.000988
	(0.00717)	(0.00673)	(0.00887)	(0.00839)
Constant	-0.00762	-0.0100	0.103	0.105
	(0.0872)	(0.0836)	(0.0992)	(0.0962)
Area dummies	Yes	Yes	Yes	Yes
Observations	182	182	182	182
R-squared	0.108		0.063	
F test model		166.3		166.3

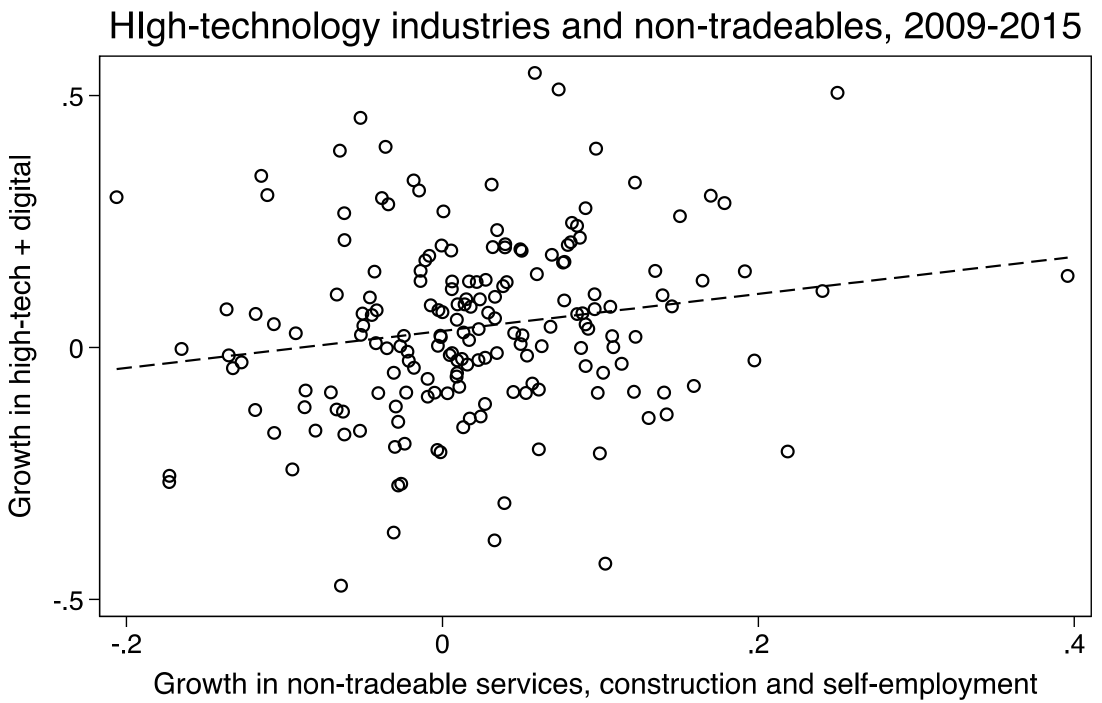
Note: Standard errors reported in parentheses, clustered on region. Dependent variable: growth in hourly pay for low skilled (columns 1 – 2) or medium-skilled (columns 4-6) not working in high-tech. IV = shift share based on 2009 local industry shares and national growth rate. All models include 4 region dummies.
*p < 0.1. **p < 0.05. ***p < 0.01.

Table 5. 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**	0.164	-0.0150	-0.0363
	(0.187)	(0.177)	(0.175)	(0.215)
High-skilled workers (%), 2009	-0.0990	0.245	1.357***	0.762**
	(0.480)	(0.483)	(0.417)	(0.385)
Unemployment rate (%), 2009	1.183	0.139	1.049	1.781
	(1.197)	(1.098)	(0.989)	(1.248)
Total employment (ln), 2009	-0.0288	0.0773***	-0.0558***	-0.0243
	(0.0265)	(0.0268)	(0.0207)	(0.0229)
Constant	0.351	-1.189***	0.448*	0.0202
	(0.307)	(0.307)	(0.251)	(0.305)
Area dummies	Yes	Yes	Yes	Yes
Observations	182	182	182	182
First stage F test	102.9	102.9	102.9	102.9
Multiplier	0.58	-	-	-

All models estimated at 2SLS. Instrument is Bartik shift-share.
Dependent variable: employment and self-employment by skill group (excluding high-technology)
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. High-technology industries versus non-tradeables employment, 2009-2015



Source: BRES 2009, 2015 and authors' adaptation. Each dot represents one of 182 travel-to-work areas.

Appendix A. Sectoral definitions

Appendix A. High-technology industry definitions

Digital tech	
26.11	Manufacture of electronic components
26.12	Manufacture of loaded electronic boards
26.20	Manufacture of computers and peripheral equipment
26.30	Manufacture of communication equipment
26.40	Manufacture of consumer electronics
26.80	Manufacture of magnetic and optical media
46.51	Wholesale of computers, computer peripheral equipment and software
46.52	Wholesale of electronic and telecommunications equipment and parts
58.21	Publishing of computer games
58.29	Other software publishing
61.10	Wired telecommunications activities
61.30	Satellite telecommunications activities
61.90	Other telecommunications activities
62.01	Computer programming activities
62.02	Computer consultancy activities
62.03	Computer facilities management activities
62.09	Other information technology and computer service activities
63.11	Data processing, hosting and related activities
63.12	Web portals
63.91	News agency activities
63.99	Other information service activities n.e.c.
95.11	Repair of computers and peripheral equipment
95.12	Repair of communication equipment
High-technology	
06.10	Extraction of crude petroleum

09.10	Support activities for petroleum and natural gas extraction
18.20	Reproduction of recorded media
19.20	Manufacture of refined petroleum products
20.13	Manufacture of other inorganic basic chemicals
20.59	Manufacture of other chemical products n.e.c.
21.10	Manufacture of basic pharmaceutical products
21.20	Manufacture of pharmaceutical preparations
24.52	Casting of steel
26.51	Manufacture of instruments and appliances for measuring, testing and navigation
26.60	Manufacture of irradiation, electromedical and electrotherapeutic equipment
26.70	Manufacture of optical instruments and photographic equipment
27.52	Manufacture of non-electric domestic appliances
28.11	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
28.94	Manufacture of machinery for textile, apparel and leather production
30.30	Manufacture of air and spacecraft and related machinery
33.16	Repair and maintenance of aircraft and spacecraft
35.11	Production of electricity
42.21	Construction of utility projects for fluids
42.22	Construction of utility projects for electricity and telecommunications
42.99	Construction of other civil engineering projects n.e.c.
49.20	Freight rail transport
49.50	Transport via pipeline
71.12	Engineering activities and related technical consultancy
71.20	Technical testing and analysis
72.11	Research and experimental development on biotechnology
72.19	Other research and experimental development on natural sciences and engineering
72.20	Research and experimental development on social sciences and humanities
74.90	Other professional, scientific and technical activities n.e.c.
91.04	Botanical and zoological gardens and nature reserve activities

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