Neil Lee and Andrés Rodríguez-Pose

Is there trickle-down from tech? Poverty, employment and the high-technology multiplier in US cities

Article (Accepted version)
(Refereed)

Original citation: Lee, Neil and Rodríguez-Pose, Andrés (2016) *Is there trickle-down from tech? Poverty, employment and the high-technology multiplier in US cities.* Annals of the Association of American Geographers, 106 (5). pp. 1114-1134. ISSN 0004-5608
DOI: 10.1080/24694452.2016.1184081

Is there trickle-down from tech? Poverty, employment and the high-technology multiplier in US cities

Neil Lee and **Andrés Rodríguez-Pose**

Department of Geography and Environment
London School of Economics
Houghton St
London WC2A 2AE, UK

Forthcoming in Annals of the Association of American Geographers

Abstract

High-technology industries are seen as important in helping urban economies thrive, but at the same time they are often considered as potential drivers of poverty and social exclusion. However, little research has assessed how high-tech affects urban poverty and the wages of workers at the bottom of the pyramid. This paper addresses this gap in the literature and investigates the relationship between employment in high-tech industries, poverty and the labour market for non-degree educated workers using a panel of 295 Metropolitan Statistical Areas (MSAs) in the United States between 2005 and 2011. The results of the analysis show no real impact of the presence of high-technology industries on poverty. Yet there is strong evidence that tech-employment increases wages for non-degree educated workers and, to a lesser extent, employment for those without degrees. These results suggest that while tech employment has some role in improving welfare for non-degree educated workers, tech-employment alone is not be enough to reduce poverty.

Keywords: High-technology industries, employment, wages, poverty, cities
JEL: R11, R12, R58

Acknowledgements

Data accessed through the Integrated Public Use Microdata (IPUMS) Service at the University of Minnesota. Alix Cocude provided excellent research assistance on this project, while Callum Wilkie drew the maps. The authors appreciate the financial support of the European Research Council under the European Union's Seventh Framework Programme (FP7/2007-2013)/ERC grant agreement nº 269868.

1. Introduction

High-technology industries are seen as a vital part of the new economy. Tech firms have the potential to achieve economies of scale, high productivity levels, and rapid growth. For those employed in the sector, tech-companies create high-skilled and very well-paid jobs. Even controlling for factors such as education and experience, workers in 'tech' earn a premium of around 17 percent relative to workers in other sectors (Hathaway & Kallerman, 2012). These industries are also geographically concentrated: many of the 'superstar' cities of the world economy – famously, Silicon Valley – have thriving tech-sectors (Currid & Connolly, 2008; Bieri, 2010). High-tech firms have also been regarded as powerful generators of indirect jobs. Moretti (2010) found a 'tech multiplier' equivalent to almost 5 new jobs for each additional high-tech job in a local economy. All these benefits make high-tech sectors extremely attractive for cities and regions. Areas with tech-sectors are regarded as the example to follow. As a consequence, national, state, and city-level policymakers the world over have become fascinated by high-tech and devoted considerable resources to both creating and attracting tech firms (Fallah et al., 2014).

The economic importance of the sector, its spatial concentration, and the policy emphasis to attract this type of firms raise an important question: who gains from the growth of tech-employment in a city? An optimistic body of research stresses that the benefits from high-tech go well beyond those employed in the sector, reaching out to the rest of the city and playing an important role in not only generating overall growth, but also reducing poverty. Sachs (2003), for example, suggests that innovation and new technology has the potential to significantly reduce overall poverty, while Glasmeier (1991) has documented the importance of high-technology industries in tackling poverty in disadvantaged rural economies. And the 'knowledge spillovers' generated by the sector are perceived to benefit entrepreneurs and workers in other sectors, with their wages increasing as a result (Echeverri-Carroll and Ayala, 2009).

However, this optimistic take on the impact of high-tech is far from dominant. Different strands of research take a more pessimistic view and some classic studies of cities with strong tech-economies have often suggested a darker side to high-tech growth. Thirty years ago Saxenian (1984) already highlighted the presence of a divided labour market in

Silicon Valley. A decade later Harrison (1994: 309) suggested that the success of Silicon Valley was in part driven by inequality and stratified local labour markets, which were "studiously ignored" in boosterist economic narratives. More recently, Florida (2005) has noted the high and growing levels of inequality in Silicon Valley. Direct employment in high-technology industries tend to require high levels of education (Hecker, 2005). These studies suggest that tech-employment is unlikely to benefit those at risk of poverty and that tech-led growth will instead result in inequality. Similar concerns are reflected by work by Sassen (2005), who argued that the dominant global cities of the world economy had increasingly polarized employment structures, with low-wage service workers employed to service the affluent workers in the urban elite.

Yet, despite the wide body of research on the tech sector, most work dealing with its impact on poverty and inequality has been conducted on individual or a comparison of case studies. Limited research has considered the impact of high-tech employment on poverty across a broad range of cities. This paper addresses this gap through an analysis of the link between high-technology employment, on the one hand, and poverty and the evolution of wages of the low-skilled, on the other, in US cities for the period between 2005 and 2011. Our principal research question is whether growth in high-technology industries is associated with a reduction in poverty. We also investigate the impact of high-technology employment on the labour market for those without degree level qualifications. We do this using the American Community Survey (ACS), a survey giving data on 295 Metropolitan Statistical Areas (MSAs, henceforth 'cities') in the United States. We focus first on the links between innovation, high-technology and poverty, before considering both wages and employment effects. We believe we are the first to do so in a panel regression format and using an instrumental variables (IV) approach to address the potential of endogeneity.

The paper has two central findings. First, we show no evidence that high-technology industries reduce poverty, whether measured by the normal poverty line or by an indicator of 'extreme' poverty. Second, we demonstrate that there is an impact of high-tech on the wages of non-degree educated workers. In short, our results suggest that there are, by and large, important benefits from attracting and/or generating high-tech employment on the wider urban economy in the US, but that these are not enough to reduce poverty and may come at the price of increased inequality.

The paper makes a number of contributions to the literature on 'inclusive growth' and the research investigating the extent to which economic development strategies benefit low-wage groups (e.g. Breau, Kogler, & Bolton, 2014; Donegan & Lowe, 2008; Fowler & Kleit, 2013; Lee, 2011; Lee & Rodríguez-Pose, 2013). It also makes a number of more specific contributions to the literature. It is the first to consider the influence of tech on poverty, focusing both on overall poverty and on the channels through which poverty may be reduced (i.e. new employment or higher wages). It uses panel data, as well as an instrumental variable approach, addressing some concerns about endogeneity which may cause problems in cross-sectional work (Echeverri-Carroll & Ayala, 2009). Finally, it also contributes to the growing evidence reaped by geographers on the link between technological change and inequality (e.g. Rigby & Breau, 2008)

The remainder of the paper is structured as follows. Section two considers the economic role of 'tech' and the potential ways in which the benefits of the sector may 'trickle-down'. Section three discusses the data and definitions of both tech-employment and poverty. Section four presents the model and a series of regression results on the link between tech and poverty. Section five considers the relationship with employment rates and wages for low-educated workers. Section six concludes with implications for research and practice.

2. High-technology, growth, and poverty

High-technology industries represent a growing share of GDP in many countries, including the US (Hathaway & Kallerman, 2012). The economic geography of these industries has been the subject of considerable research (Currid & Connolly, 2008), with the importance of tacit knowledge and the need to hire workers with highly specific and often unique skills meaning that firms in the high-tech sector tend to concentrate spatially in a limited number of cities (Bieri, 2010; Fallah et al., 2014). These are factors which have been known in academic and policy circles for some time and have triggered a race to create and attract high-tech firms as the formula for achieving local economic development and economic success. Many cities have consciously followed Florida's (2002, 2005, 2014) three T's recipe for economic development: 'technology, talent, and tolerance'. Cities that manage to attract technology and talent and brew a tolerant environment are more likely to become high tech hubs, replicating the success experienced in the last decades of the 20th century by the well-known cases of the Silicon Valley and Route 128, the two key tech-hubs in the US (Saxenian, 1994). While these two cases differ significantly from one another,[1] they outline how the tech-industry, aligned with a supportive military, could create thriving economic clusters. Many cities the world over have put in place policies aiming to replicate their success.

The key factor behind the multiplication of public policies aimed at promoting high-tech in cities is the increasingly strong evidence base on the importance of high-technology firms for wages and employment. These effects are both internal and external to the sector. Wages within the sector are high and employment has been growing for quite some time (Hall & Kahn, 2008; Hathaway & Kallerman, 2012). There may also be *external* wage or employment effects from tech employment into other sectors of the local economy. Explanations for these external effects have considered the potential of 'multiplier' effects or cross-sectoral knowledge spillovers. But who exactly benefits from these external 'multiplier' effects? Do the benefits of the externalities from high-tech benefit the whole of society or only those with high-skills? Is there any evidence of high-tech firms influencing the job opportunities and wages of those at the greatest risk of poverty in urban contexts?

The idea that there are multiplier effects from the growth of one sector in a regional economy is a basic tenet of regional economics. Moretti (2010) and Moretti & Thulin (2013) recently applied this concept to the tech-sector. They suggested that growth in tradeable industries in a local economy may lead to knock-on growth in others, often non-tradeable sectors in the same local economy. These new jobs may be in supply chains or associated employment in personal services or retail, due to increased consumer demand. The largest multipliers, they find, are in high-technology industries – in part because of the affluence of the workers in this sector. According to their research, each additional tech-job in the local economy (narrowly defined as those in Machinery and Computing Equipment, Electrical Machinery, and Professional Equipment) is associated with the creation of a long-run additional 4.9 non-tradeable jobs.

[1] Route 128 was structured around a few large firms, while Silicon Valley was based on a model of networked firms, with fewer large firms dominating (Saxenian, 1994).

Work in the literature on human capital spillovers has also begun to break down the processes driving these multipliers. Kaplanis (2010a; 2010b) suggested that the presence of high-skilled residents may have three effects: (1) it may increase consumption demand; (2) it can create production complementarities where low and high skilled workers aid each other in the labour market; and (3) it may create production spillovers, increasing productivity. These production spillovers have been the focus of considerable research. Rauch (1993) showed that high-skilled workers raised wages for other nearby workers, even when those workers were less skilled. Kaplanis (2010a; 2010b) used British data in order to demonstrate the existence of both increased wages and employment chances for low skilled workers in local labour markets with more skilled workers.

Knowledge spillovers may be particularly important in urban environments in the case of high-tech industries (Fallah et al., 2014). Echeverri-Carroll and Ayala (2009), in particular, have indicated that there is an overall 'tech-city wage premium' in cities with high shares of tech-employment. Yet this premium is more likely to benefit those with higher skills, as it is larger for college-educated workers (6.4%) than for non-college educated workers (4.2%). As their research only presented an average effect across all non-college educated workers, it can be assumed that any premium may be even lower for those combining low skills with low incomes. There is also a potential selection bias as low skilled workers in 'tech-cities' may be more likely to be in employment, a factor that would bias down estimates of wages for other groups. Other work has also shown external wage effects from local concentrations of workers with Science, Technology, Engineering and Maths (STEM) degrees (Winters, 2014).

These two effects – increased wages and increased employment – are the main mechanisms through which the strength of the local labour market effects may reduce poverty. Yet there is little direct evidence on the link between tech employment and poverty. In a related paper, Fowler & Kleit (2013) show that the presence of industrial clusters is associated with a lower poverty rate in non-metropolitan commuting zones, but not in metropolitan areas. Relative to rural areas, US cities offer greater economic opportunities and often have lower poverty rates (Fisher, 2007).

Other authors have considered the impact of the tech-sector on inequality. Florida and Mellander (2014) studied the determinants of wage inequality in a cross-section of US MSAs and found that the share of high-technology industries is a reliable predictor of wage inequality, if not income inequality. Panel studies have also unveiled a positive relationship between innovation and inequality for European regions (Lee & Rodríguez-Pose, 2013; Lee, 2011) and Canadian cities (Breau et al., 2014). This was, however, not the case of US cities (Lee & Rodríguez-Pose, 2013), where higher levels of innovation were not connected to a rise in interpersonal inequality. This evidence, nevertheless, was based on an admittedly limited panel of US cities.

In this paper we examine the effect of the presence of high-tech firms on those at the bottom of the pyramid, in terms of being at a greater risk of poverty, having low skills, or commanding the lowest wages. We analyse the weight of high-tech on both poverty and extreme poverty in a total of 295 US metropolitan regions over the period between 2005 and 2011, as well as the connection between high-technology and levels of employment for those with limited formal qualifications.

3. Data, variables and definitions

The data

The data are taken from American Community Survey (ACS) Microdata. The information is accessed via the IPUMS service at the University of Minnesota (Ruggles et al., 2010). The ACS is a large-scale annual survey of US households with a sample of more than 2 million individuals each year – essentially a (weighted) sample of 1 in 100 of the population (for more information on its strengths and limitations, see Spielman and Singleton, 2015). For this study, we use the microdata and construct indicators at the Metropolitan Statistical Area (MSA) level. However, data for one indicator – population – are not included in the ACS dataset. To address this, we amalgamate county level population data to the boundaries of ACS MSAs. Note that this is not a perfect process. as there are problems matching the population data for two MSAs.[2] Robustness tests show that the exclusion of these MSAs does not significantly alter the results.

Measuring poverty

[2] The MSAs we exclude are Grand Junction, CO & Hattiesburg, MS

The measure of poverty used in this research is the share of family units in the MSA whose income is below the poverty line, as defined by the US Social Security Administration. The unit is the family (for adults living alone the figure is given for the individual) and, as is standard, the data is weighted in order to take family size into account (the figure then being lower for individuals than parents of large families). The IPUMS data give family income as a share of the poverty line. Our core indicator is the poverty rate - the share of families with incomes below the official poverty line. The official poverty line in the US is defined according to a historic method based on availability of food, but uprated according to cost of living (although the cost of living does not vary by city). Data is equivalised according to both the size of family and number of resident children aged under 18 years old.

The US poverty line is relatively tightly defined, there are important concerns that thresholds for poverty are low, arbitrary and lacking geographical variation (Greenberg, 2009). To address these concerns and give a fuller indicator of how tech impacts on incomes, we also calculate measures for the share of families with incomes below each percentage of the poverty line (for example, share of families with an income below 150% of the poverty line). Figure 1 depicts the distribution of households in poverty across US MSAs. The greatest incidence of poverty is found in southern states and, especially, in Texas. In this state McAllen-Edinburg-Mission, Brownsville-Harlingen, and Laredo topped the ranks in 2011 as the MSAs with the highest incidence of poverty (Figure 1). Urban poverty was also rife in other southern states and, most notably, Georgia, as well as in some of the rustbelt states, such as Illinois, Indiana, and Ohio. Some MSAs in California (e.g. Fresno and Visalia-Porterville) and Arizona also featured amongst those with the highest incidence of poverty in the country. By contrast, MSAs in the north-east – in a corridor expanding between Virginia Beach, Virginia, and Portland, Maine – were amongst those with the lowest levels of poverty in the country (Figure 1).

Insert Figure 1 around here

Given that our sample includes the great recession, it is also important to show how these change over time. The mean poverty rate across all cities in our sample stays relatively constant for the period 2005 - 2008 (it is 13.7% in 2005; 13.6% in 2008). But there is then a sharp jump to 15.0% in 2009, 16.0% in 2010 and 16.5% in 2011. In contrast, the average share of tech changed little in the period. On average, 4.5% of employment was in tech in 2005, this peaked at 4.6% before the crisis but fell to only 4.3% by 2011.

To identify the potential channels through which tech-employment may benefit low-education locals, we also test our models with two alternative indicators. The two main channels through which tech-employment may reduce poverty are through increased wages (consistent with a knowledge spillover explanation or simply one of increased local demand for labour) or job creation (consistent with 'multipliers'). The two indicators are (3) wages for low skilled workers – defined as the mean wage for these workers and (4) the employment rate for low skilled workers. We define less educated workers as those without degree level qualifications.

Defining the 'high-tech' economy

There is no single definition of the high-tech economy. The US Bureau of Labour Statistics (Hecker, 2005) suggests four ways of identifying high-tech sectors: those with a high share of scientists, engineers and technicians in their workforces; high employment in Research and Development (R&D); those which produce high-tech products, or; those using high-tech production methods. Perhaps because of data limitations, the former approach has been most common. For example, Markusen et al. (1986) used an occupational definition, where 'high-tech' is identified as those industries with higher than average shares in occupations such as scientists, engineers, computer scientists, or geologists. Yet occupational approaches do not always produce intuitive definitions and even using objective criteria does not address the fact that some sectors (i.e. computing) seem more 'tech' than others (i.e. some parts of machinery) (Glasmeier, 1991).

For the purpose of our analysis, we resort to an approach which has become common in academic and policy circles and adopt the definition used by Fallah et al. (2014), derived, in turn, from Hecker (2005). Fallah et al. (2014) identify five industrial categories – biotech, ICT services, ICT manufacturing, information tech and natural resources – as the components of a high-tech sector. We make some minor amendments to their definition. First, as our main concern is on the urban literature on 'tech', we exclude the natural resources component included in Fallah et al.'s (2014) definition,. Second, we cannot perfectly match all sectors used in the definition because of differences in industry coding in the ACS. These differences are, however, small and are unlikely to affect the results. Full details on the definition of high-tech used are included in Appendix A.

Insert Table 1 and Figure 2 around here

Table 1 gives the list of the top and bottom ten high-tech cities in the US, as identified by our indicator. As would be expected given the literature on the geography of tech, there is a relatively uneven distribution of tech employment, with San Jose in California far higher than any other city in the country, with almost a quarter of all employment in high-tech sectors. Following this there is a set of other cities with strong tech-employment, including Seattle-Everett and Nashua. Most high-tech cities in the US are located along a north-eastern corridor, running from Nashua in New Hampshire to Raleigh in North Carolina, as well as along the Pacific coast, from Seattle (Washington) to San Diego (California). There are, however, exceptions with some MSAs in the interior of the US with high levels of high-tech employment (Figure 2). These include Wichita (Kansas), Boulder (Colorado), Santa Fe (New Mexico), Cedar Rapids (Iowa), and Austin (Texas), which in 2011 were amongst the top 10 Tech cities in the US. Even more striking is the case of Huntsville (Alabama), which came third in the country on the basis of aerospace and military technology industries, as an oasis in an area mainly devoid of tech (Figure 2). Other relatively isolated MSAs with a large percentage of tech employment were Boise (Idaho), Rochester (Minnesota), Madison (Wisconsin), or Palm Bay (Florida). There is less of a clear pattern among the MSAs at the bottom of the tech classification, although many of them are concentrated in southern and Great Plains states and tend to be relatively small in size (Figure 2).

Insert figures 3 – 7 around here

What is the geography of our core variables? Figures 3 – 7 give scatterplots between the key variables of tech employment, poverty, and employment and wages for those without degrees. To identify geographical variation, we also consider MSA population as an additional variable. Figure 4 shows that larger cities tend to have higher shares of tech employment, with a statistically significant and positive relationship (even when controlling for San Jose, the outlier). Larger cities also tend to have lower poverty rates, although the slope is shallower the relationship remains statistically significant ($p<0.000$). Figures 6 and 7 show the relationship between tech employment, and employment rates and wages for workers without degrees. They show that cities with greater shares of tech employment have higher wages but not higher employment rates for workers without degrees. Only the former relationship is statistically significant.

4. Model, controls and results

Model

Our basic regression model links the share of high-technology employment in the local economy with household poverty. Because there are likely to be time-invariant city level factors which will affect our results, we estimate the models as fixed effects models. We also cluster the standard errors by MSA to adjust for serial correlation. The basic model is as follows:

$$POV_{it} = \alpha + \beta_1 \, TECH_{it} + \beta_2 \, EDUC_{it} + \beta_3 \, DEMOG_{it} + \beta_4 \, CITYSIZE_{it} + \beta_5 \, MAN_{it} + \varepsilon + \delta \qquad (1)$$

For each MSA ‘i’ where time ‘t’ is a year between 2005 – 2011. Where:

POV is a measure of the share of households in either poverty or extreme poverty,

TECH is the share of employment in high-technology sectors,

EDUC is a measure of the share of the population with a 4 year degree,

DEMOG is a set of demographic controls for gender, race, share of children in the population and migrants,

CITYSIZE is the log of total population,

MAN, is the share of employment in manufacturing.

The time invariant error is ‘ε’ and the remaining error is ‘δ’. In addition, in all specifications we include year dummies. These should control for changes in the national economy which will influence poverty rates. Table 2 provides the variable description and summary statistics for each of the variables included in the analysis.

We also include year fixed effects in all models. This will control for cyclical changes in the US poverty rate and are particularly important given the rise in poverty rates associated with the great recession and documented above.

When looking at the correlation between our two variables of interest – tech employment and poverty rates at MSA level – a simple correlation highlights a potential negative association between both. As depicted in Figure 3, in 2011 MSAs with a higher level of employment in tech also had lower rates of household poverty. This, however, may be a spurious relationship as other factors which may affect poverty need to be taken into account.

Insert Figure 3 around here

In addition, this correlation may be subject to a potential problem of endogeneity. This can happen if poverty is associated with reduced local demand, consequently lowering the potential of high-technology growth. Another potential reason for endogeneity may be that growth in high-tech employment may lead to selective migration, attracting workers currently in poverty. To address this problem, we also resort to an instrumental variables (IV) approach. Our instrument is a version of the common shift-share instrument used by, amongst others, Ottaviano and Peri (2005) which builds on the likely association between initial industry share and subsequent growth. We take initial employment in each of the four 'tech' industries in 2005 and assume they grow according to the national rate of growth of each sector over the subsequent period. The variable is the predicted share of tech-employment in a city. This should be associated with tech-growth, but unrelated to changes in poverty in the period.

Control variables

In addition to TECH, our control variables account for both demographic influences and influences related to the size or industrial structure of the city. We first control for the levels of human capital of the population with a variable for the share of the population with a 4-year degree. We expect this to be negatively associated with poverty for two reasons. First, as they earn more cash those with high-skill levels are unlikely to be in poverty themselves – unless they remain unemployed for long periods of time. There may also be external effects from human capital on other parts of the urban labour market, with skilled workers creating jobs for others both directly (through entrepreneurship or within firms) and indirectly (via their higher spending in the local economy) (Heuermann, Halfdanarson, & Suedekum, 2010; Kaplanis, 2010a).

We also control for migration which may also have dual effects. Migrants to the US tend to be polarised into both relatively high and relatively low education groups. Depending on the composition of the migrants, the expectations are for more low-skilled workers and, as a consequence, higher poverty rates. Migrants may also face discrimination in the labour market and find it harder to find high wage formal employment. This can occur even in high-tech industries: Hall and Kahn (2008) show immigrants in high-technology industries or occupations in Canada actually earn less than non-migrants. Yet in contrast, a growing body of evidence highlights the economic medium- and, increasingly, long-term importance of migrants to cities and regions (Ottaviano & Peri, 2005; Rodríguez-Pose & von Berlepsch, 2014, 2015). Migrants bring new ideas, can help build international links and are particularly likely to be motivated and entrepreneurial. They also transmit this dynamism and entrepreneurialism to the territories where they settled in the US (Rodríguez-Pose & von Berlepsch, 2014), leaving long-lasting economic benefits. Because of this dual effect, the impact of migration on poverty rates can be considered as ambiguous.

An additional variable is the share of population who are non-white. Non-white groups may face discrimination in the labour market and there is a wide literature on the historic challenges faced by some non-whites in the United States (Wilson, 1987). Poverty rates are higher for non-whites (Macartney et al., 2013). To account for this, we also include a variable for the share of the population who are non-white.

Chances of poverty vary through the life course. In particular, the period after having children is generally associated with poverty as having and raising children both (a) raise costs (for food and childcare), but can also (b) reduce labour force participation and job choice and, consequently, wages. Our use of an equivalised measure of poverty should address (a), but we nevertheless still expect a positive association between the share of young people in the population and poverty. In contrast, wages and employment rates for males are generally higher than those for women in the US. We include a control for this to capture this association.

Two city specific factors are also included in the analysis. The first is city size, measured as the log of total population. Larger cities may offer greater opportunities to enter the labour market and the density of economic activity is generally associated with higher productivity and wages. Greater job access and higher wages at the top end of the scale are likely to reduce poverty. Finally, the type of jobs available will shape poverty rates. While there are multiple sectors which could be investigated, the key sector in this context is manufacturing which is seen as offering well paid employment for relatively low skilled workers and has traditionally been associated with lower poverty rates. We therefore include a final control for the share of workers employed in manufacturing. This is calculated as all manufacturing employment, excluding those in the high-technology manufacturing category.

Results: Tech employment and poverty

Table 3 presents the results of the first set of regressions which consider the relationship between tech employment and poverty. Columns 1 – 3 introduce the results of the fixed effects panel data estimations. Column 1 displays the association between the percentage of tech employment and the percentage of households in poverty in US MSAs; column 2 includes a number of demographic controls into the estimation; while column 3 adds the controls for city size and industrial structure. Columns 4 – 6 repeat the same structure for the IV analysis, using the shift share variable as instrument. All models include year dummies and are estimated with fixed effects.

Insert Table 3 around here

The main finding of the analysis is the lack of relationship between employment in tech and poverty. The relationship is negative in the fixed effects specifications, while it becomes positive in the IV. In neither case the coefficients are significant, meaning that tech employment does not seem to have an influence on the levels of household poverty experience in US cities. In contrast to the expectations of the optimistic literature, it does not appear that increasing tech employment in a city is associated with any meaningful reduction in poverty. This finding is reinforced by the strength of our instrument in the IV regressions. The predicted share of tech-employment in a city appears to be a good predictor of subsequent increases in poverty – the Kleibergen-Paap test, (considered the best indicator of instrument validity when using robust standard errors) is above the threshold values and far above the rule of thumb indicator of 10. Yet the IV results do not significantly alter those of the fixed effect panel data analysis, reinforcing the idea of a lack of association between tech-employment and poverty.[3]

The control variables by contrast, do yield some sights into the determinants of urban poverty in the US. First and foremost, human capital matters for poverty. The share of the population with a degree is associated with reduced poverty and this coefficient remains negative and significant in the IV analysis, implying that the higher the percentage of the population with a university degree, the lower the likelihood of poverty affecting cities in America. In contrast, high concentrations of children are, as expected, associated with higher urban poverty levels. There is no relationship between migration, gender, and industrial structure and urban household poverty.

The lack of association between the overall household poverty and tech employment may not necessarily mean that there is no connection whatsoever between both phenomena. It may be the case that tech employment can be increasing wages for the very poorest – potentially dragging households and individuals out of extreme poverty, without generating enough additional income to take them over the poverty line. To test whether this is the case in Table 4 repeats the regressions in Table 3, considering only with a measure of extreme poverty – the percentage of households below 75% of the poverty line – is our dependent variable.

Insert Table 4 around here

[3] A reviewer makes the sensible point that there may be a non-linearity in the relationship between tech and poverty. We experiment with a variety of model specifications to investigate this possibility, but cannot find such a relationship. A second challenge is that year on year variation may not be sufficient for any relationship to be apparent. However, estimating the regressions using only the end years of the period does not alter the results significantly.

As before, the insignificant coefficients for the tech employment variable underline the absence of a robust relationship between tech and poverty, regardless of the threshold of poverty considered. The control variables perform similarly as in Table 3 (extreme poverty declines with the percentage of the population with higher education and increases with the share of children living in a city), but, despite an increase in the size of the coefficient, any effect of tech employment on poverty remains trivial.

5. Wages and employment for the non-degree educated

While our results do not show any impact of tech-employment on poverty overall, there may be other mechanisms through which tech affects the low-skilled urban labour market, especially through its potential influence on wages and levels of employment for those at the bottom of the pyramid. We attempt to isolate these effects in Tables 5 and 6. Table 5 assesses the relationship between low skilled wages and tech-employment; Table 6 consists of the same model with low skilled employment rates as the dependent variable. The tables follow exactly the same structure as Tables 3 and 4. Kaplanis (2010b) identifies three ways in which skilled workers may affect the salaries and employment of low skilled workers: consumption demand, production complementarities, or production spillovers. Similarly, Moretti (2010) shows that the presence of tech-multipliers will spread throughout society. In each case, the result would be felt in terms of either increased wages or increased employment for low-qualified workers. In both cases we use workers with low qualifications, as these are most likely to be at risk of poverty and least likely to be working in tech.

Insert Table 5 around here

Table 5 considers the relationship between tech employment and wages for non-degree educated workers.[4] We focus on these groups for two reasons: less well educated workers are more likely to be in poverty, and they are less likely to work in high-tech sectors. In contrast to the results with household poverty as the dependent variable (Tables 3 and 4), we find a positive and statistically significant relationship between tech employment and the hourly wages for non-degree educated workers. Regardless of the number of controls included in the analysis and of the method used, the coefficient for tech employment is

[4] We focus on those qualified below Associate Degree level.

always positive and significant, meaning that in US cities with a high degree of tech employment, the salaries of the less educated workers tend to be higher than in cities where this is not the case (Table 5). So while the effects of tech do not seem to reach those in poverty or extreme poverty, they do affect the wages of those with the lowest level of education. In our basic specification (Table 5, Column 1), a 1 percent increase in tech employment in a city is associated with a 2.9 percent increase in wages for non-degree educated workers. The IV analysis reduces the effect to levels of 1.9 percent (Table 5, Columns 4-6), but the coefficients always point to the existence of a solidly robust and positive causal relationship between cities with a greater share of tech employment and increases in the wages of those with the lowest levels of education.

The controls in the IV analysis indicate that the wages of those with the lowest level of education in urban America are affected by factors which are not always the same as those influencing poverty levels. While the percentage of the population with a university degree is no longer significant, in what seems to be a reproduction of the traditional 'male breadwinner' model, the wages of those at the bottom of the pyramid are positively affected by the percentage of children in a city, the percentage of men, and the share of manufacturing (Table 5, Columns 4-6).

Insert Table 6 around here

The results for employment are more nuanced (Table 6). There has been considerable discussion of the potential for 'tech multipliers' with multiplier jobs being created in jobs with strong tech economies. Our fixed effects results support this interpretation to some degree, with a positive and statistically significant relationship between tech employment and the employment rate for less well educated workers. Yet the IV does not support this interpretation. All IV coefficients for tech employment remain positive, but become not significant (Table 6).

7. Conclusions

High-tech has been traditionally regarded by academics and policymakers alike as a key factor behind urban growth and development. Cities not only in the US, but across the world, have become engaged in races to make the city more high-tech (Rodríguez-Pose and Hardy, 2014). However, the impact of the presence of high tech on those at the bottom of the pyramid is still poorly understood. While we know little about how high-tech affects urban inequality, we know next to nothing about its impact on overall poverty. On the one hand, an optimistic body of research heralds high-technology industries as having the potential to help urban economies thrive, but also to raise wages and reduce poverty. On the other, a more pessimistic set of studies highlights the potential difficulties of tech-led urban growth: that the benefits of the sector may be skewed, and that the result of growth in the tech-sector may not trickle-down to those at risk of poverty. This paper has tested these ideas with using a panel of US cities over the period 2005 – 2011, a period which saw significant increases in poverty but a relatively resilient tech sector. Our results reveal a more complex and nuanced picture. While technology industries are associated with rising wages for low skilled workers, the benefits of tech on wages are not enough to reduce the poverty rate. Tech alone does not seem to be a remedy for those living in poverty, let alone in extreme poverty in urban environments in the US.

The results have some significant implications for policy. For local economic development practitioners, chasing tech-employment may lead to aggregate gains, but – if it is to reach deprived groups – needs to be combined with efforts to ensure these gains are widely shared. Options for doing this might include skills training or targeted support to help those in poverty into employment. There has been renewed interest in geographical dimensions of policy to address low pay and precarity (Wills and Linneker, 2014). The localised nature of tech-growth suggests an important policy area in linking employment growth with disadvantaged groups. This will vary according to specific local geographical variation in labour markets and patterns of transport and housing. These results also provide some challenges for tech firms. Given the growing scale of the sector, its resources and – in many cases – the profitability of tech firms, there is clearly more which could be done by tech-firms to help address poverty in the local economies in which they are based.

This paper has made a number of contributions to the literature on the gains from growth, yet it opens up a number of potential future areas for research. First, our data includes a period of significant economic crisis. While we can control for this using time fixed effects, one extension would be to develop a panel with a longer time period. Second, our results are at an aggregate level – other work may want to dig into the microdata to investigate the relationships which are driving wage growth but not poverty reduction (for example, by considering the types of group who benefit from growth in the tech sector. Linking longitudinal individual level data with local economic characteristics would be a good way of doing this. A fourth useful extension would be to correct out indicator of poverty for cost of living in a manner such as that used by Essletzbichler (2015). Finally, our research is for the United States – a relatively high-tech, high-poverty economy – future research may wish to test if these results apply in different economic and institutional circumstances.

Bibliography

Bieri, D. S. (2010). Booming Bohemia? Evidence from the US High-Technology Industry. *Industry & Innovation*, *17*(1), 23–48. http://doi.org/10.1080/13662710903573828

Breau, S., Kogler, K. C., & Bolton, K. (2014). On the Relationship between Innovation and Wage Inequality: New Evidence from Canadian Cities. *Economic Geography*, DOI: 10.1111/ecge.12056.

Currid, E. & Connolly, J. (2008). Patterns of Knowledge: The Geography of Advanced Services and the Case of Art and Culture. *Annals of the Association of American Geographers,* 98 (2): 414-434.

Donegan, M., & Lowe, N. (2008). Inequality in the Creative City: Is There Still a Place for "Old-Fashioned" Institutions? *Economic Development Quarterly*, *22*(1), 46–62. http://doi.org/10.1177/0891242407310722

Echeverri-Carroll, E., & Ayala, S. G. (2009). Wage differentials and the spatial concentration of high-technology industries. *Papers in Regional Science*, *88*(3), 623–641. http://doi.org/10.1111/j.1435-5957.2008.00199.x

Essletzbichler, J. (2015) The top 1% in US metropolitan areas. *Applied Geography,* 61, 35-46.

Fallah, B., Partridge, M. D., & Rickman, D. S. (2014). Geography and high-tech employment growth in US counties. *Journal of Economic Geography*, *14*(September 2013), 683–720. http://doi.org/10.1093/jeg/lbt030

Fisher, M. (2007). Why Is U. S. Poverty Higher in Nonmetropolitan than in Metropolitan Areas ? *Growth and Change*, *38*(1), 56–76.

Florida, R., & Mellander, C. (2014). The Geography of Inequality: Difference and Determinants of Wage and Income Inequality across US Metros. *Regional Studies*, *0*(February 2015), 1–14. http://doi.org/10.1080/00343404.2014.884275

Florida, R. (2002). *The Rise of the Creative Class. And How It's Transforming Work, Leisure and Everyday Life*. New York: Basic Books.

Florida, R. (2005). *The Flight of the Creative Class. The new global competition for talent.* London: Harper Collins.

Florida, R. (2014). "The creative class and economic development", *Economic Development Quarterly,* 28 (3): 196-205.

Fowler, C., & Kleit, R. (2013). The Effects of Industrial Clusters on the Poverty Rate. *Economic Geography,* 90(2), 129-154.

Glasmeier, A. (1991). *The High-Tech Potential: Economic Development in Rural America*. Transaction Publishers, New Jersey.

Greenberg, M. (2009). It's time for a better poverty measure. *Centre for American Progress.* Available from: https://cdn.americanprogress.org/wp-content/uploads/issues/2009/08/pdf/better_poverty_measure.pdf

Harrison, B. (1994). Lean and Mean: The changing landscape of corporate power in the age of flexibility. New York: Guilford.

Hall, P. V. & Khan, A. (2008). Differences in hi-tech immigrant earnings and wages across Canadian cities. *The Canadian Geographer,* 52 (3): 271-290.

Hathaway, I., & Kallerman, P. (2012). Technology Works : High-Tech Employment and Wages in the United States. *Bay Area Council Economic Institute*, (December).

Hecker, D. E. (2005). High-technology employment: a NAICS-based update. *Monthly Labour Review,* July: 57 – 72.

Heuermann, D., Halfdanarson, B., & Suedekum, J. (2010). Human Capital Externalities and the Urban Wage Premium: Two Literatures and their Interrelations. *Urban Studies*, *47*(4), 749–767. http://doi.org/10.1177/0042098009352363

Kaplanis, I. (2010a). Local human capital and its impact on local employment chances in Britain, (January). *Spatial Economics Research Centre Working Paper, 40*. Retrieved from: http://eprints.lse.ac.uk/33503/1/sercdp0040.pdf

Kaplanis, I. (2010b). Wage Effects from Changes in Local Human Capital in Britain. *Spatial Economics Research Centre Working Paper*, 39. Retrieved from http://eprints.lse.ac.uk/33615/

Lee, N. (2011). Are innovative regions more unequal? Evidence from Europe. *Environment and Planning C: Government and Policy*, *29*(1), 2–23. http://doi.org/10.1068/c1046r

Lee, N., & Rodríguez-Pose, A. (2013). Innovation and spatial inequality in Europe and USA. *Journal of Economic Geography*, *13*(1), 1–22. http://doi.org/10.1093/jeg/lbs022

Markusen, A. R., Hall, P. H., & Glasmeier, A. (1986). *High tech America: the what, how, where, and why of the sunrise industries*. Boston: Allen & Unwin.

Moretti, B. E. (2010). Local Multipliers, *American Economic Review: Papers and Proceedings,* 100 (May), 1–5.

Moretti, E., & Thulin, P. (2013). Local multipliers and human capital in the United States and Sweden. *Industrial and Corporate Change*, *22*(1), 339–362. http://doi.org/10.1093/icc/dts051

Ottaviano, G., & Peri, G. (2005). The economic value of cultural diversity: evidence from US cities. *Journal of Economic Geography*, *6*(1), 9–44. http://doi.org/10.1093/jeg/lbi002

Rauch, J. E. (1993). Productivity gains from geographic concentration of human capital: evidence from the cities. *Journal of Urban Economics*, *34*, 380–400.

Rigby, D., & Breau, S. (2008). Impacts of Trade on Wage Inequality in Los Angeles: Analysis Using Matched Employer–Employee Data. *Annals of the Association of American Geographers*, *98*(4), 920–940. http://doi.org/10.1080/00045600802219786

Rodríguez-Pose, A., & von Berlepsch, V. (2014) When migrants rule: the legacy of mass migration on economic development in the US. *Annals of the Association of American Geographers 104*(3), 628-651.

Rodríguez-Pose, A. and von Berlepsch, V. (2015) European migration, national origin and long-term economic development in the United States. *Economic Geography* (forthcoming).

Rodríguez-Pose, A. and Hardy, D. (2014) *Technology and industrial parks in emerging countries: panacea or pipedream?* Heidelberg and New York: Springer, 110 pp.

Ruggles, S., Alexander, J. T., Genadek, K., Goeken, R., Schroeder, M. B., & Sobek, M. (2010). Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota.

Sachs, J. (2003). "The Global Innovation Divide" in Jaffe, A., Lerner, J., and Stern, S. (eds.) *Innovation Policy and the Economy.* Boston: MIT Press, 131 – 141.

Sassen, S. (2005). *Cities in a World Economy,* London: Sage.

Saxenian, A. (1984). The urban contradictions of Silicon Valley : regional growth and the restructuring of the semiconductor industry. *Sunbelt/snowbelt: Urban Development and Regional Restructuring*, 237–62. http://doi.org/10.1111/j.1468-2427.1983.tb00592.x

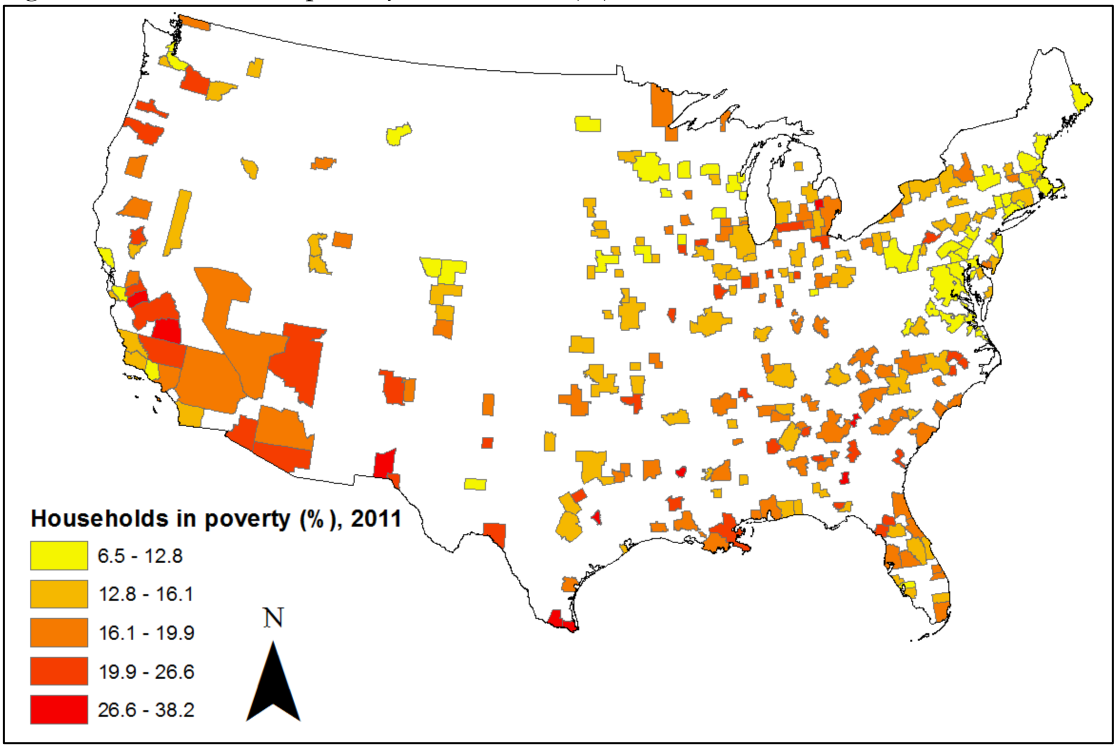
Saxenian, A. (1994). *Regional Competitive Advantage: Culture and Competition in Silicon Valley and Route 128*. Cambridge MA: Harvard University Press.

Spielman, S. E. & Singleton, A. (2015) Studying Neighborhoods Using Uncertain Data from the American Community Survey: A Contextual Approach, *Annals of the Association of American Geographers*, 105:5, 1003-1025

Wills, J. & Linneker, B. (2014) In-work poverty and the living wage in the United Kingdom: a geographical perspective. *Transactions of the Institute of British Geographers*, 39: 2, 182–194.

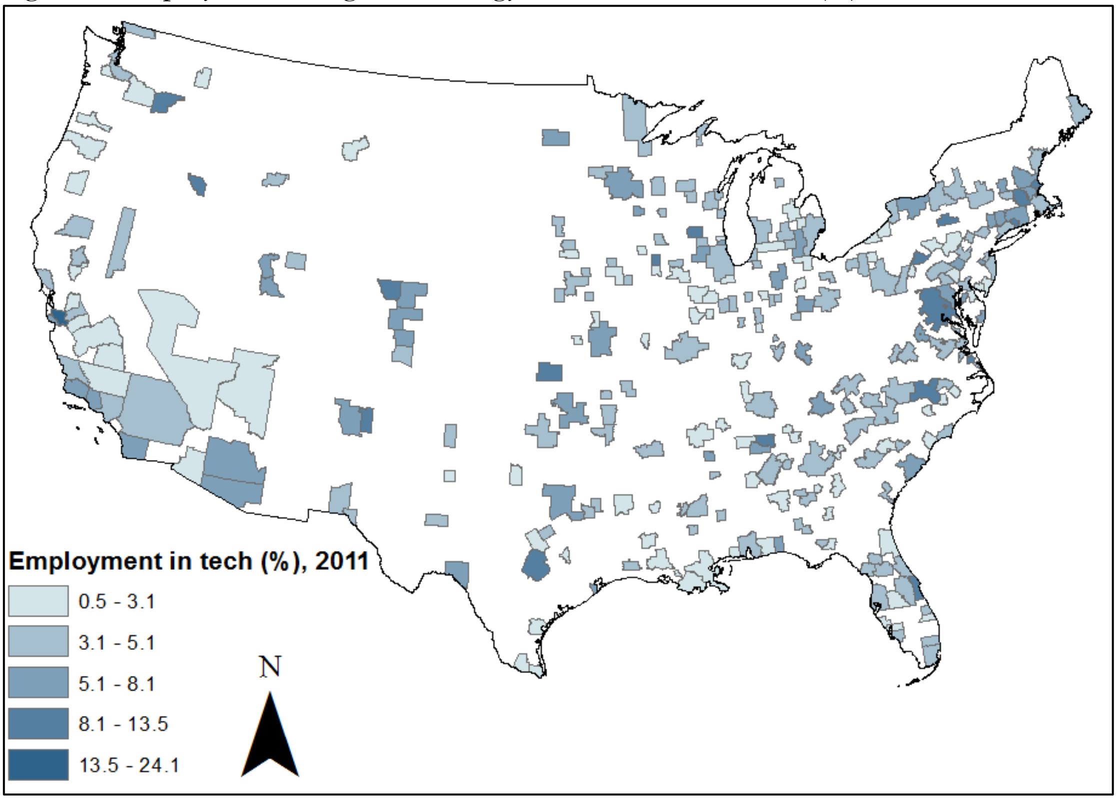
Winters, J. V. (2014). STEM graduates, human capital externalities, and wages in the U.S. *Regional Science and Urban Economics*, *48*, 190–198. http://doi.org/10.1016/j.regsciurbeco.2014.07.003

Figure 1. Households in poverty in US MSAs (%), 2011



Source: American Community Survey via IPUMS.

Figure 2. Employment in high-technology industries in US MSAs (%), 2011



Source: American Community Survey via IPUMS.

Figure 3. Tech employment and poverty rates, 2011

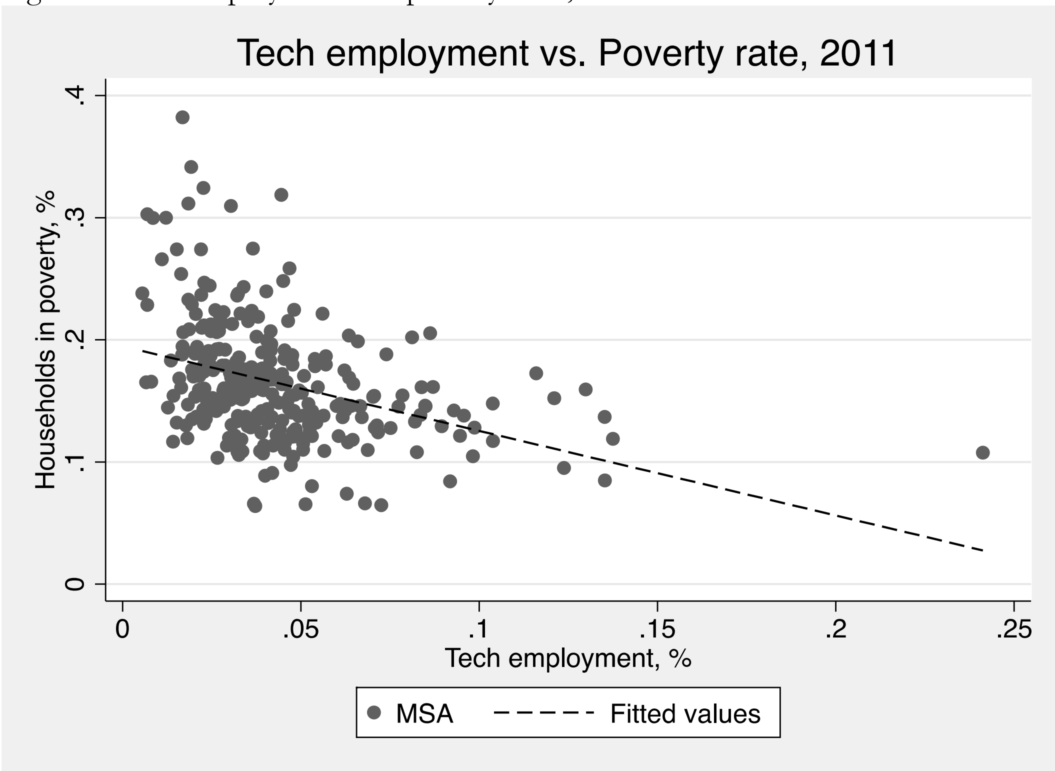


Figure 4. Tech employment and MSA population, 2011

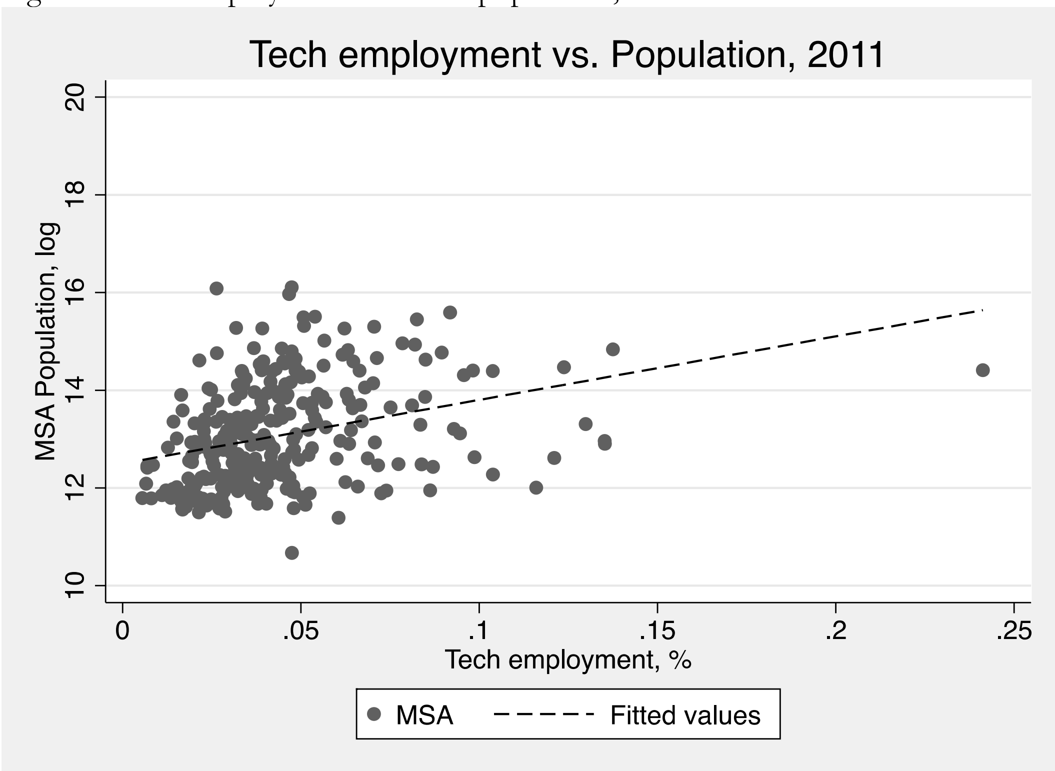


Figure 5. Poverty rates and MSA population, 2011

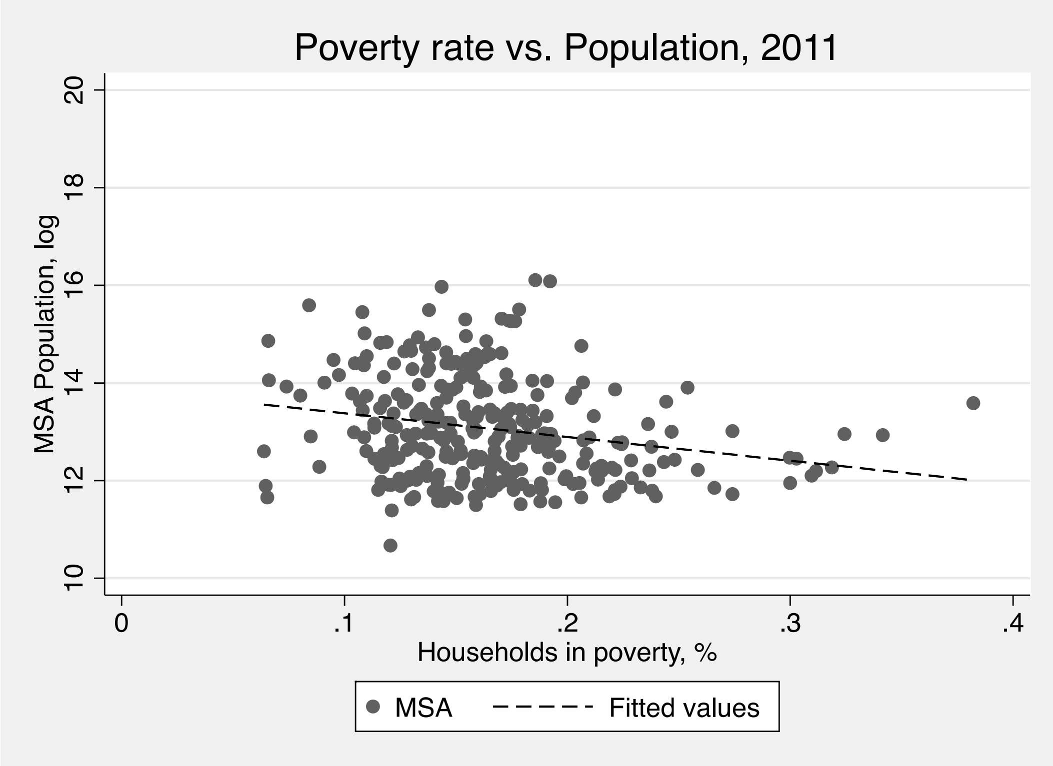


Figure 6. Tech employment and wages for non-degree educated workers, 2011

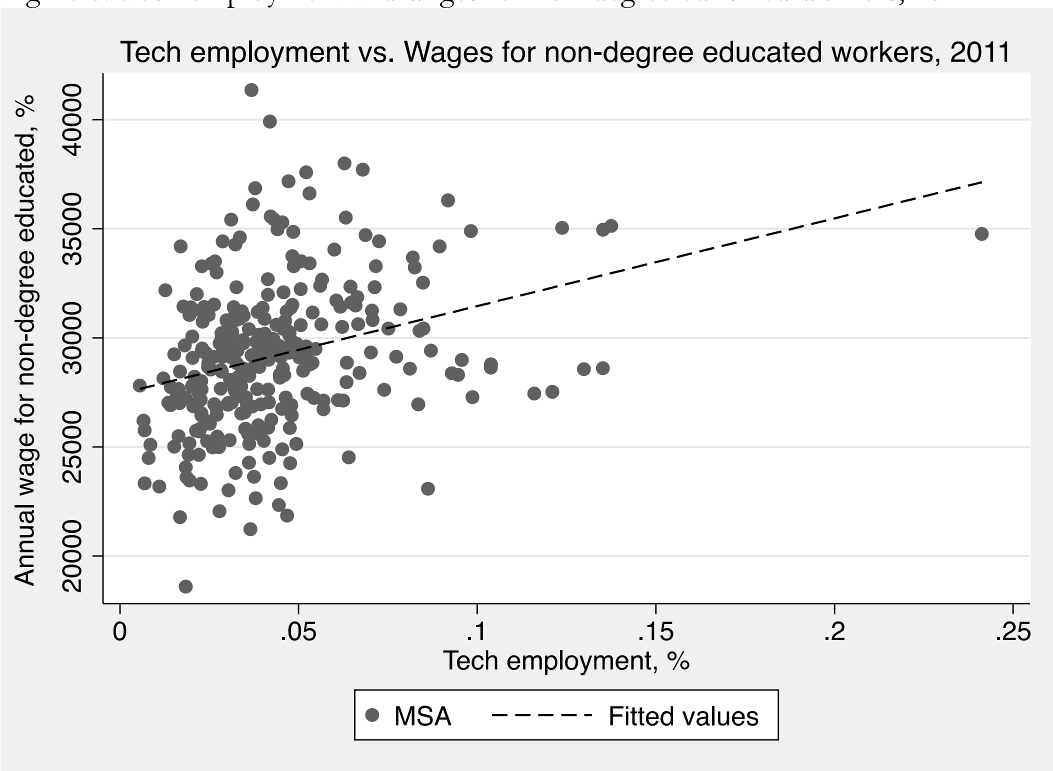


Figure 7. Tech employment and employment rates for non-degree educated workers, 2011

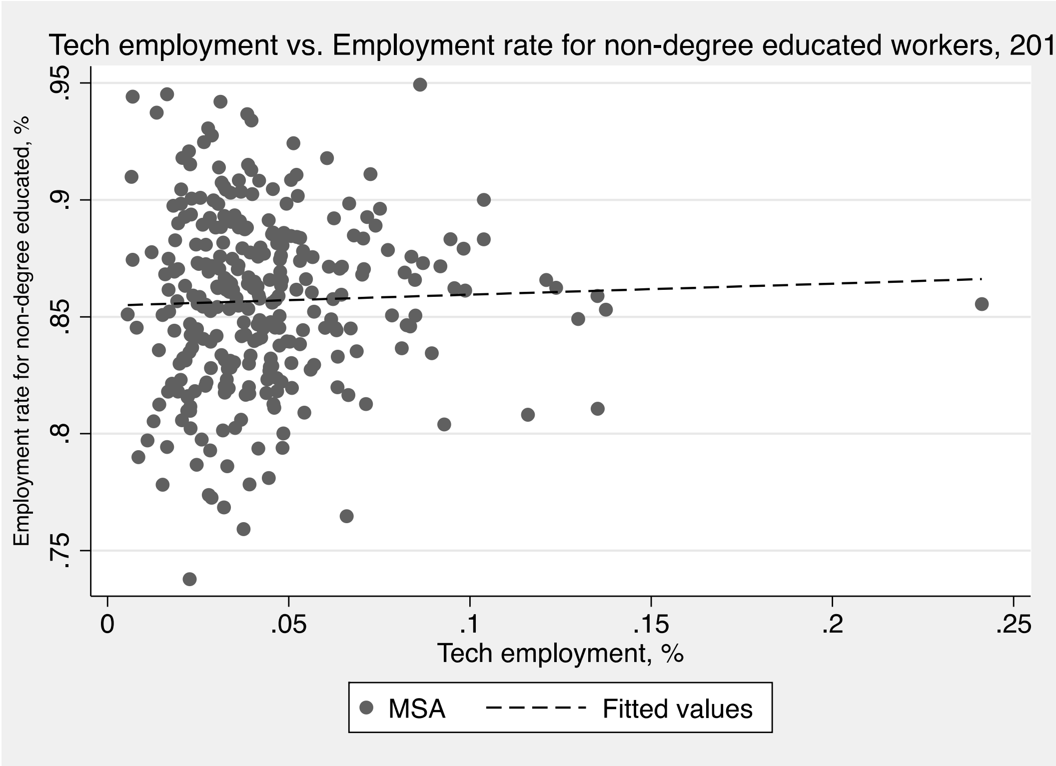


Table 1. High-tech and low-tech cities, 2011

Rank	**MSA**	**% tech employment**	**Rank**	**MSA**	**% tech employment**
1.	San Jose, CA	24.1	286.	Abilene, TX	1.4
2.	Seattle-Everett, WA	13.8	287.	Atlantic City, NJ	1.3
3.	Nashua, NH	13.5	288.	Monroe, LA	1.2
4.	Huntsville, AL	13.5	289.	Bloomington, IN	1.1
5.	Wichita, KS	13.0	290.	Merced, CA	0.9
6.	Lowell, MA/NH	12.4	291.	Waterloo-Cedar Falls, IA	0.8
7.	Boulder-Longmont, CO	12.1	292.	Laredo, TX	0.7
8.	Santa Fe, NM	11.6	293.	Yakima, WA	0.7
9.	Cedar Rapids, IA	10.4	294.	Jacksonville, NC	0.6
10.	Austin, TX	10.4	295.	Alexandria, LA	0.5

Mean: 4.3%
Source: American Community Survey.

Table 2. Variable description and summary statistics, 2011

	Obs	Mean	St Dev	Min	Max
Poverty rate (%)	295	0.16	0.05	0.06	0.38
Low skilled wage rate ($)	295	29,198	3,394	18,594	41,356
Low skilled employment rate (%)	295	0.86	0.04	0.74	0.95
% Tech employment	295	0.04	0.03	0.01	0.24
% Not US born	295	0.10	0.08	0.01	0.49
% Non white	295	0.18	0.12	0.02	0.77
% of pop <16	295	0.28	0.03	0.21	0.39
% of pop male	295	0.52	0.01	0.48	0.59
% with degree	295	0.24	0.07	0.08	0.51
Population	295	881,850	1,315,988	43,055	9,889,025
% Manufacturing Emp	295	0.08	0.05	0.00	0.35

Source: American Community Survey, except Population which is developed through county data via the American FactFinder.

Table 3. Tech-employment and poverty - Regression results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Households in poverty (%), ln					
Estimation method	Fixed effects	Fixed effects	Fixed effects	IV	IV	IV
Tech employment (%)	-0.0133	-0.00695	-0.00536	0.190	0.169	0.153
	(0.0229)	(0.0229)	(0.0232)	(0.167)	(0.160)	(0.159)
% with degree (ln)		-0.169***	-0.170***		-0.192***	-0.191***
		(0.0475)	(0.0471)		(0.0547)	(0.0538)
% Not US born (ln)		-0.00436	-0.00585		-0.00443	-0.00602
		(0.0245)	(0.0247)		(0.0245)	(0.0246)
% Non white (ln)		-0.00559	-0.00552		-0.00395	-0.00407
		(0.0106)	(0.0103)		(0.0113)	(0.0108)
% of pop <16 (ln)		0.212	0.237*		0.245*	0.269**
		(0.131)	(0.130)		(0.126)	(0.126)
Male (%)		-0.194	-0.184		-0.329	-0.304
		(0.463)	(0.454)		(0.466)	(0.460)
Population (ln)			-0.457**			-0.483**
			(0.189)			(0.190)
Manufacturing % (ln)			0.00934			0.0136
			(0.0243)			(0.0248)
Constant	-2.075***	-1.954***	4.039			
	(0.0532)	(0.325)	(2.535)			
Observations	2,065	2,065	2,065	2,065	2,065	2,065
R-squared	0.347	0.355	0.359	0.306	0.324	0.334
Number of MSA	295	295	295	295	295	295
KP Wald F-test				27.540	20.214	20.251
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Estimated as fixed effects models (columns 1 – 3) or using an instrumental variable (4 – 6) with robust standard errors (in parentheses). Standard errors clustered by metropolitan statistical area (MSA). All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Different levels of poverty and tech employment, Instrumental Variable Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Percentage households below each percent of poverty line:															
Dependent variable	50%	60%	70%	80%	90%	Poverty line	110%	120%	130%	140%	150%	160%	170%	180%	190%	200%
Tech employment (%)	0.382	0.418	0.0349*	0.0196	0.0295	0.0321	0.0205	0.0144	0.0106	-0.119	-0.201*	-0.0122	-0.164	-0.198*	-0.216**	-0.211**
	(0.288)	(0.274)	(0.0200)	(0.0204)	(0.0212)	(0.0221)	(0.0218)	(0.0227)	(0.0229)	(0.108)	(0.108)	(0.0250)	(0.107)	(0.109)	(0.105)	(0.0948)
% with degree (ln)	-0.259***	-0.259***	-0.0302***	-0.0311***	-0.0373***	-0.0385***	-0.0380***	-0.0400***	-0.0463***	-0.173***	-0.153***	-0.0528***	-0.156***	-0.146***	-0.145***	-0.150***
	(0.0905)	(0.0888)	(0.00849)	(0.00826)	(0.00902)	(0.00915)	(0.00886)	(0.00886)	(0.00921)	(0.0396)	(0.0378)	(0.00923)	(0.0330)	(0.0328)	(0.0308)	(0.0288)
% Not US born (ln)	-0.0131	-0.0113	-0.000793	-0.000440	-0.00154	-0.00148	-0.000137	0.000638	0.000582	-0.0104	-0.00587	-0.00169	-0.0115	-0.0119	-0.0120	-0.0159
	(0.0322)	(0.0323)	(0.00262)	(0.00251)	(0.00267)	(0.00303)	(0.00296)	(0.00297)	(0.00301)	(0.0140)	(0.0152)	(0.00325)	(0.0131)	(0.0126)	(0.0123)	(0.0113)
% Non-White (ln)	0.00204	0.00580	0.00207	0.00171	0.00174	0.00191	0.00209	0.00210	0.00114	-0.00301	-0.00284	0.00127	-0.000669	0.00125	0.00225	0.00106
	(0.0149)	(0.0143)	(0.00139)	(0.00151)	(0.00157)	(0.00165)	(0.00176)	(0.00175)	(0.00177)	(0.00798)	(0.00746)	(0.00173)	(0.00675)	(0.00658)	(0.00627)	(0.00599)
% of pop <16 (ln)	0.259	0.289	0.0314*	0.0323*	0.0382**	0.0414**	0.0338*	0.0352*	0.0363*	0.103	0.0838	0.0295	0.0541	0.0648	0.0731	0.0809
	(0.191)	(0.178)	(0.0170)	(0.0186)	(0.0193)	(0.0193)	(0.0205)	(0.0190)	(0.0199)	(0.0926)	(0.0945)	(0.0193)	(0.0807)	(0.0771)	(0.0740)	(0.0718)
Male (%)	-0.216	-0.493	2.08e-06	-0.00460	-0.0550	-0.0410	-0.0628	-0.0485	-0.0710	-0.263	-0.209	-0.0608	-0.168	-0.139	-0.116	-0.135
	(0.670)	(0.618)	(0.0549)	(0.0638)	(0.0639)	(0.0662)	(0.0711)	(0.0729)	(0.0696)	(0.345)	(0.343)	(0.0730)	(0.297)	(0.298)	(0.284)	(0.261)
Population (ln)	-0.506**	-0.495**	-0.0269	-0.0490*	-0.0474*	-0.0525*	-0.0484	-0.0515	-0.0595*	-0.337**	-0.364**	-0.0890**	-0.407***	-0.406***	-0.392***	-0.400***
	(0.248)	(0.247)	(0.0255)	(0.0282)	(0.0285)	(0.0294)	(0.0308)	(0.0315)	(0.0318)	(0.153)	(0.145)	(0.0355)	(0.134)	(0.128)	(0.120)	(0.106)
Manufacturing % (ln)	0.0418	0.0632**	0.00438	0.00256	0.000506	0.000224	0.00101	0.000847	0.000572	-0.00313	-0.00327	-0.00148	-0.00821	-0.00707	-0.00347	-0.00692
	(0.0313)	(0.0316)	(0.00277)	(0.00315)	(0.00377)	(0.00384)	(0.00396)	(0.00394)	(0.00400)	(0.0199)	(0.0189)	(0.00425)	(0.0170)	(0.0158)	(0.0157)	(0.0140)
Observations	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065	2,065
R-squared	0.332	0.280	0.255	0.294	0.302	0.293	0.327	0.343	0.346	0.383	0.339	0.392	0.364	0.370	0.333	0.335
Number of metaread	295	295	295	295	295	295	295	295	295	295	295	295	295	295	295	295
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Estimated as fixed effects instrumental variable model with robust standard errors (in parentheses). All models include year dummies.
IV = shift-share based on growth in tech sub-sectors. Kleibergen-Paap F statistic = 18.672 for all models.
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Tech employment and wage for non-degree educated workers

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Hourly wage for non-degree educated workers (ln)					
Estimation method	Fixed effects	Fixed effects	Fixed effects	IV	IV	IV
Tech employment (%)	0.0288***	0.0261***	0.0262***	0.193***	0.178***	0.182***
	(0.00948)	(0.00958)	(0.00940)	(0.0702)	(0.0655)	(0.0655)
% with degree (ln)		0.0209	0.0222		0.000972	0.00190
		(0.0206)	(0.0207)		(0.0259)	(0.0260)
% Not US born (ln)		0.00252	0.00284		0.00246	0.00268
		(0.00785)	(0.00777)		(0.00966)	(0.00966)
% Non-White (ln)		-0.00912**	-0.00937**		-0.00770*	-0.00796*
		(0.00435)	(0.00436)		(0.00462)	(0.00470)
% of pop <16 (ln)		0.0619	0.0504		0.0911**	0.0812*
		(0.0395)	(0.0398)		(0.0436)	(0.0449)
Male (%)		0.740***	0.748***		0.623***	0.630***
		(0.152)	(0.154)		(0.180)	(0.183)
Population (ln)			0.128*			0.102
			(0.0728)			(0.0783)
Manufacturing % (ln)			0.0194**			0.0236***
			(0.00757)			(0.00900)
Constant	10.27***	9.985***	8.355***			
	(0.0216)	(0.103)	(0.951)			
Observations	2,065	2,065	2,065	2,065	2,065	2,065
R-squared	0.337	0.356	0.360	0.152	0.198	0.195
Number of MSA	295	295	295	295	295	295
KP Wald F-test				18.428	18.657	18.672
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Estimated as fixed effects models (columns 1 – 3) or using an instrumental variable (4 – 6) with robust standard errors (in parentheses). Standard errors clustered by metropolitan statistical area (MSA). All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Tech employment and the employment rate for non-degree educated workers

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Employment rate, non-degree educated workers (ln)					
Estimation method	Fixed effects	Fixed effects	Fixed effects	IV	IV	IV
Tech employment (%)	0.00984**	0.00829*	0.00817*	0.0399	0.0305	0.0313
	(0.00471)	(0.00459)	(0.00460)	(0.0327)	(0.0319)	(0.0317)
% with degree (ln)		0.0146	0.0147		0.0117	0.0116
		(0.0109)	(0.0110)		(0.0123)	(0.0123)
% Not US born (ln)		0.00601	0.00611		0.00600	0.00609*
		(0.00377)	(0.00375)		(0.00371)	(0.00369)
% Non White (ln)		-0.00713***	-0.00712***		-0.00692***	-0.00691***
		(0.00240)	(0.00239)		(0.00243)	(0.00242)
% of pop <16 (ln)		-0.00634	-0.00789		-0.00204	-0.00331
		(0.0269)	(0.0272)		(0.0275)	(0.0279)
Male (%)		0.234**	0.233**		0.217**	0.215**
		(0.0980)	(0.0974)		(0.101)	(0.100)
Population (ln)			0.0302			0.0264
			(0.0414)			(0.0416)
Manufacturing % (ln)			-0.00132			-0.000698
			(0.00513)			(0.00512)
Constant	-0.0833***	-0.180***	-0.578			
	(0.0109)	(0.0660)	(0.550)			
Observations	2,065	2,065	2,065	2,065	2,065	2,065
R-squared	0.599	0.607	0.608	0.588	0.601	0.601
Number of MSA	295	295	295	295	295	295
KP Wald F-test				18.428	18.657	18.672
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Estimated as fixed effects models (columns 1 – 3) or using an instrumental variable (4 – 6) with robust standard errors (in parentheses). Standard errors clustered by metropolitan statistical area (MSA). All models include year dummies.
*** p<0.01, ** p<0.05, * p<0.1

Appendix A1. Definition of high-tech employment in ACS

Definition used by Fallah et al. (2014)		**Our definition**	
NAICS code	**Definition**	**ACS Code**	**Definition**
Biotechnology			
3254	Pharmaceutical and medicine manufacturing	3254	Pharmaceutical and medicine manufacturing
Natural resources			
1131,1132	Forestry	-	
2111	Oil and gas extraction	-	
3241	Petroleum and coal products manufacturing	-	
Information			
5415	Computer systems design and related services	5415	Computer systems design and related services
3333	Commercial and service industry machinery manufacturing	3333	Commercial and service industry machinery manufacturing
3342	Communications equipment manufacturing	334M1	Communications, audio, and video equipment (3342, 3343)
3344	Semiconductor and other electronic component manufacturing	334M2	Electronic components and products, n.e.c.
3345	Navigational, measuring, electromedical and control instruments manufacturing	3345	Navigational, measuring, electromedical, and control instruments
5112	Software publishers	5112	Software publishing
5161	Internet publishing and broadcasting	5161	
5179	Other telecommunications	517Z	Other telecommunication services (2003-2007) Telecommunications, except wired telecommunications carriers (2008-onward)
5181	Internet service providers and Web search portals	5181	Internet service providers and Web search portals
5182	Data processing, hosting and related services	5182	
3343	Audio and video equipment manufacturing	334M1	Communications, audio, and video equipment
3346	Manufacturing and reproducing, magnetic and optical media	334M2	Electronic components and products, n.e.c.
4234	Professional and commercial equipment and supplies, merchant wholesalers	4234	Professional and commercial equipment and supplies
5416	Management, scientific and technical consulting services	5416	Management, scientific and technical consulting services
5171	Wired telecommunications carriers	5171	Wired telecommunications carriers
5172	Wireless telecommunications carriers (except satellite)	5172	Included as 5179
5173	Telecommunications resellers	5173	Included as 5179
5174	Satellite telecommunications	5174	Professional and commercial equipment and supplies
8112	Electronic and precision equipment repair and maintenance	8112	Electronic and precision equipment repair and maintenance
Manufacturing			
3341	Computer and peripheral equipment manufacturing	3341	Computer and peripheral equipment manufacturing
3254	Pharmaceutical and medicine manufacturing	3254	Pharmaceuticals and medicines
3251	Basic chemical manufacturing	325M	Industrial and miscellaneous chemicals (also 3259)
3252	Resin, synthetic rubber and artificial synthetic fibers and filaments	3252	Resin, synthetic rubber and artificial synthetic fibers and filaments manufacturing

	manufacturing			
3255	Paint, coating and adhesive manufacturing	3255	Paint, coating and adhesive manufacturing	
3259	Other chemical products and preparation manufacturing	325M	Industrial and miscellaneous chemicals (also 3251)	
3332	Industrial machinery manufacturing	333M	Machinery n.e.c. (3332, 3334 & 3339)	
3333	Commercial and service industry machinery manufacturing	3333	Commercial and service industry machinery	
3336	Engine, turbine and power transmission equipment manufacturing	3336	Engine, turbine and power transmission equipment manufacturing	
3339	Other general purpose machinery manufacturing	333M	Machinery, n.e.c. (3332, 3334, 3339)	
3341	Computer and peripheral equipment manufacturing	3341	Computer and peripheral equipment manufacturing	
3342	Communications equipment manufacturing	334M1	Communications, audio, and video equipment(3342, 3343)	
3343	Audio and video equipment manufacturing	334M1	Communications, audio, and video equipment(3342, 3343)	
3344	Semiconductor and other electronic component manufacturing	334M2	Electronic components and products, n.e.c (3344, 3346)	
3345	Navigational, measuring, electromedical and control instruments manufacturing	3345	Navigational, measuring, electromedical and control instruments manufacturing	
3346	Manufacturing and reproducing, magnetic and optical media	334M2	Electronic components and products, n.e.c (3344, 3346)	
3353	Electrical equipment manufacturing	335M	Electrical machinery, equipment, and supplies, n.e.c. (2003-2007) Electric lighting, and electrical equipment manufacturing, and other electrical component manufacturing, n.e.c. (2008-onward), (3351, 3353, 3359)	
3364	Aerospace product and parts manufacturing	33641M1 33641M2	Aircraft and parts (336411-336413 Aerospace products and parts (336414-336419)	
3369	Other transportation equipment manufacturing	3369	Other transportation equipment	
3241	Petroleum and coal products manufacturing	32411 3241M	Petroleum refining (32411) Miscellaneous petroleum and coal products (32412, 32419)	
3253	Pesticide, fertilizer and other agricultural chemical manufacturing	3253	Agricultural chemicals	
Services				
4234	Professional and commercial equipment and supplies, merchant wholesalers	4234	Professional and commercial equipment and supplies, merchant wholesalers	
4861	Pipeline transportation of crude oil	486	Pipeline transportation	
4862	Pipeline transportation of natural gas	486	Pipeline transportation	
4869	Other pipeline transportation	486	Pipeline transportation	
5112	Software publishers	5112	Software publishers	
5161	Internet publishing and broadcasting	5161	Internet publishing and broadcasting	
5171	Wired telecommunications carriers	5171	Wired telecommunications carriers	
5172	Wireless telecommunications carriers (except satellite)	517Z	Other telecommunication services (2003-2007) or Telecommunications, except wired telecommunications carriers (2008-onward) (5133 exc. 51331)	
5173	Telecommunications resellers	517Z	Other telecommunication services (2003-2007) or Telecommunications, except wired telecommunications carriers (2008-onward) (5133 exc. 51331)	
5174	Satellite telecommunications	517Z	Other telecommunication services (2003-2007) or Telecommunications, except wired telecommunications carriers (2008-onward) (5133 exc. 51331)	
5179	Other telecommunications	517Z	Other telecommunication services (2003-2007) or Telecommunications, except wired telecommunications carriers (2008-onward) (5133 exc. 51331)	
5181	Internet service providers and Web search portals	5181	Internet service providers and Web search portals	5181
5182	Data processing, hosting and related services	5182	Data processing, hosting and related services	
5211	Software publishers	5112	Software publishing	
5232	Securities and commodity exchanges	52M2	Securities, commodities, funds, trusts, and other financial investments (523, 525)	

5413	Architectural, engineering and related services	5413	Architectural, engineering, and related services
5415	Computer systems design and related services	5415	Computer systems design and related services
5416	Management, scientific and technical consulting services	5416	Management, scientific and technical consulting services
5417	Scientific research and development services	5417	Scientific research and development services
5511	Management of companies and enterprises	55	Management of companies and enterprises
5612	Facilities support services	561M	Other administrative, and other support services (5611, 5612, 5619)
8112	Electronic and precision equipment repair and maintenance	8112	Electronic and precision equipment repair and maintenance