The World's Rust Belts: The Heterogeneous Effects of Deindustrialization on 1,993 Cities in Six Countries

Luisa Gagliardi, Enrico Moretti, Michel Serafinelli*

September 2023

Abstract

We use a newly-assembled dataset to investigate the employment consequences of deindustrialization for 1,993 cities in France, Germany, Great Britain, Italy, Japan and the United States. In all six countries we find a strong negative relationship between a city's share of manufacturing employment in the year of its country's manufacturing peak and the subsequent change in the city's total employment, reflecting the fact that cities where manufacturing was initially more important experienced larger negative labor demand shocks. But in a significant number of cases, total employment fully recovered and even exceeded initial levels, despite the loss of manufacturing jobs. Overall, 34% of former manufacturing hubs–defined as cities with an initial manufacturing employment share in the top tercile–experienced employment growth faster than their country's mean, suggesting that a surprisingly large number of cities was able to adapt to the negative shock caused by deindustrialization. We then seek to understand why some former manufacturing hubs recovered while others didn't. We find that deindustrialization had different effects on local employment depending on the initial share of college educated workers in the labor force. While in the two decades before the manufacturing peak, cities with a high college share experienced a rate of employment growth similar to those with a low college share, in the decades after the manufacturing peak, the employment trends diverge: cities with a high college share experienced significantly faster employment growth. The divergence grows over time at an accelerating rate. Using an instrumental variable based on the driving distance to *historical* colleges and universities, we estimate that total employment in a city at the 75th percentile of its country's college share distribution grew 9.6 percentage points faster per decade than total employment in a city at the 25th percentile. An important reason was a faster growth in human capital-intensive services, which more than offset the loss of manufacturing jobs.

*Gagliardi: Bocconi University; Moretti: University of California, Berkeley; Serafinelli: University of Essex. We thank Giacomo De Giorgi, Ed Glaeser, Gordon Hanson, Richard Jin, Paolo Pinotti, Anna Raute, Perihan Saygin, Daniela Sonedda, Alex Whalley, Yikai Wang and seminar participants at Armenian Economic Association, Bocconi, CEA, CReAM, EEA, EBRD, Essen, Essex, Florida, Groningen, ISER, LSE, Mainz, Milano, RCEA, Sorbonne, Vienna, Zurich, and the UK Cabinet Office's Open Innovation Team for helfpul comments, and Eike J Eser, Zhexin Feng, Benjamin Couillard, Daniel Edgel, Thomas King, Diana Rivera, Genet Zinabou for excellent research assistance. We thank Emanuele Ciani, Gilles Duranton, Matthias Dorner, Laurent Gobillon, Miren Lafourcade, Sachiko Kazekami for assistance with the data. Serafinelli gratefully acknowledges financial support from the UK Department for Business, Energy and Industrial Strategy. Moretti gratefully acknowledges financial support from Clausen Center for International Business and Policy.

Now Main Street's whitewashed windows and vacant stores
Seems like there ain't nobody wants to come down here no more
They're closing down the textile mill across the railroad tracks
Foreman says these jobs are going boys and they ain't coming back
Bruce Springsteen – My Hometown

1 Introduction

Over the past several decades, manufacturing employment has been declining in all industrialized countries (IMF, 2018; Benedetto, 2018). In the U.S., the number of manufacturing jobs fell from 19.7 million in 1982 to 12.5 million in 2021. Germany, France, the UK, Italy and Japan experienced similar manufacturing employment losses relative to the size of their respective labor forces.[1]

Since manufacturing is spatially concentrated, the demise of manufacturing employment has been particularly painful for areas that used to have a large share of employment in manufacturing. The Rust Belt in the United States, Northern England, and the Ruhr Valley in Germany, once among the most prosperous regions in their respective countries, have been experiencing declining economic prospects for decades. Former industrial centers like Detroit in the US, Liverpool in the UK and Duisburg in Germany have come to symbolize weak labor demand and shrinking economic opportunities. Detroit, the epitome of these trends, has been losing residents for fifty years, and its population is now at the same level that it was one hundred years ago. A third of its residents are living below the poverty line and its name has become synonymous with urban blight and seemingly irreversible decline.

These trends have generated a wealth of ideas for place-based initiatives aimed at restarting local economies in formerly industrial regions, like the US Rust Belt or Northern England.[2] The UK is currently engaging in an effort to spur investment and employment in Northern England, called "leveling-up", while Germany and France spend

[1] These declines have been driven by a combination of increases in capital intensity, technological change (Acemoglu and Restrepo, 2020) and trade with lower-wage countries (Autor, Dorn, and Hanson, 2013; Acemoglu, Autor, Dorn, Hanson, and Price, 2016; Pierce and Schott, 2016). Baily and Bosworth (2014) provide an overview of recent changes in US manufacturing employment. For the US, see also Acemoglu, Dorn, Hanson, Price, et al. (2014), Charles, Hurst, and Notowidigdo (2016), Charles, Hurst, and Notowidigdo (2019), Van Dijk (2014), Von Wachter (2010), Krueger (2017), Houseman (2018), Abraham and Kearney (2020), Weaver and Osterman (2017),Hanson and Livas (2023). For Germany, see Dauth, Findeisen, and Suedekum (2014), Dauth, Findeisen, and Suedekum (2021) and Dustmann, Fitzenberger, Schönberg, and Spitz-Oener (2018). For an overview of UK trends, see Turok and Edge (1999), Rodes (2020) and Brandily, Distefano, Donnat, Feld, Overman, and Shah (2022). For France, see Marchand and Minni (2019). For Italy, see Daniele, Malanima, and Ostuni (2018). For Japan, see Banasick and Hanham (2008). For a spatial analysis of European unemployment clusters, see Overman and Puga (2002).

[2] Recent examples include but are not limited to Wolman, Wial, Clair, and Hill (2017); Bartik (2018); Gruber and Johnson (2019); Kahn and McComas (2021); Armstrong (2021). See also Criscuolo, Martin, Overman, and Van Reenen (2018); Kantor and Whalley (2022); Garin (2019).

billions of Euros annually to support economically struggling communities (Ehrlich and Overman, 2020).

While it's clear that many local economies were hit hard by deindustrialization, it is less clear whether the best-known examples of urban decline – the Detroit's and the Liverpool's – are representative of the experience of *all* the cities in industrialized countries that used to have a strong manufacturing base. Local economies are not static entities—they are remarkably dynamic and in some cases they are able to adapt to negative shocks. The disappearance of manufacturing jobs, however initially painful, does not necessarily imply the demise of *all* communities with a manufacturing history.

Although previous studies have documented that the effects of the manufacturing decline on local communities tend to be *on average* negative and persistent (Autor et al. 2013; Charles, Hurst, and Schwartz 2019; Rice and Venables 2020; Hanson and Livas 2023), there is less empirical work that documents the spatial *heterogeneity* in these effects. In particular, there is limited evidence on how common it is for former manufacturing centers to successfully recover from the consequences of deindustrialization. And if there are indeed cases of recovery, an important and still poorly explored question is identifying which features of a local economy raise the probability of recovery.

In this paper, we study the employment consequences of deindustrialization for 1,993 cities in six countries: France, Germany, Italy, Japan, the United Kingdom, and the United States. We first provide a descriptive account of the geographic heterogeneity in employment changes during the period of deindustrialization — defined as the period between each country's peak in aggregate manufacturing employment and the end of our sample period in 2010. We focus on former manufacturing hubs—defined as Local Labor Markets that in the year of their country's manufacturing peak have a manufacturing employment share in the top tercile of their country's distribution. Within each of the six countries we uncover vast heterogeneity across cities in total employment changes during this period. While on average former manufacturing hubs lost employment after their country's manufacturing peak, a surprisingly large share in each country was able to fully recover. We then seek to understand one of the causes of such differences in labor market performance across cities within each country. We focus on differences in the initial level of human capital of local residents and their role in explaining heterogeneity in total employment growth during the years of manufacturing decline.

By studying the experience of six countries we hope to draw conclusions that are broader in scope than the ones that we would draw from one single country. While the specific estimates that we uncover vary from country to country, the findings appear qualitatively consistent across the six countries in our sample. Despite profound cross-country differences in national institutions, economic policies, historical legacies and unionization rates, the local effects of deindustrialization in our six countries appear to reflect, at least in part, common economic forces.

We use a newly assembled dataset obtained by combining and harmonizing several country-specific data sources for the six countries under consideration. Our geographic unit of analysis is the Local Labor Market (LLM). While the exact definition varies from country to country, Local Labor Markets are designed by each country's relevant statistical agency to represent geographically self-contained labor markets where most workers reside and work rather than administrative boundaries. Our dataset includes observations at the Local Labor Market level organized at decadal frequency. We use the terms Local Labor Markets and cities interchangeably.

In the first part of the paper, we document several stylized facts on the experience of Local Labor Markets within each of our six countries during the period of deindustrialization. In all six countries we find a strong negative relationship between a Local Labor Market's share of manufacturing employment in the year of its country's manufacturing peak and the subsequent change in total employment experienced by the Local Labor Market (measured in deviation from its country's average change). A pooled regression using all the cities in the six countries yields a slope of -0.169 (0.016), implying that a 1 standard deviation increase in initial manufacturing share is associated with 2.71 percent slower growth per decade in the years between the relevant country's manufacturing peak and 2010 (relative to the relevant country's average). This reflects the fact that, by definition, cities with a large initial share of manufacturing employment experienced a large negative shock to labor demand during the period of deindustrialization. This finding is consistent with previous work on the negative effects of trade-induced deindustrialization (see, for example, Autor et al. (2013).)

This average effect on local employment masks a large amount of variation across labor markets. Specifically, in all six countries we uncover a significant amount of heterogeneity in employment changes across former manufacturing hubs in the decades following the start of the manufacturing decline. Although total employment declined in many former manufacturing hubs relative to their country's mean, we find a large number of cases in which total employment grew faster than their country's mean, despite the losses of manufacturing jobs. We estimate that 34% of former manufacturing hubs in the six countries experienced an employment growth faster than their country's mean, and by 2010, had a relative employment level equal to or above the one they had in the year of the manufacturing peak. This share is remarkably high given that it is based on cities that by definition had a high initial manufacturing share and therefore experienced a large negative shock in labor demand due to deindustrialization. The share ranges from 17.2% in the US to 47.2% in Germany, with Great Britain (28.8%), France (30.3%), Japan (36.1%) and Italy (38.8%) in the middle. Essentially, we find that for each Detroit and Liverpool that loses employment, there is a former manufacturing hub where employment successfully recovers and even exceeds the level achieved in the year of the manufacturing peak.

In the second part of the paper, we study the role played by residents' initial level

of human capital in affecting the probability of employment recovery in the period of deindustrialization. Previous work has shown that over the last century, cities with many skilled residents have been more resilient to economic shocks (Glaeser and Saiz, 2004). We test the hypothesis that cities with a larger share of college graduates in the peak year of manufacturing experienced faster total employment growth in the years after the manufacturing peak compared to cities with a similar initial manufacturing share but a smaller share of college graduates.

The experience of Pittsburgh, PA–one of the most important former manufacturing hubs in the U.S.–exemplifies the hypothesis that we test. Once the capital of steel production in North America, by the 1970s Pittsburgh had become one of the Rust Belt's fastest-declining cities. But unlike many other metro areas, Pittsburgh had a strong skill base, anchored by Carnegie Mellon University and the University of Pittsburgh. When manufacturing jobs evaporated, this skill base allowed local employment to grow in different sectors, offsetting the losses in manufacturing (Andes, Horowitz, Helwig, and Katz, 2017; Mills, Elkins, Gandhi, Elanbeck, and Gillman, 2022). Today, the region's dominant tradable sector industries are human capital-intensive sectors, such as life science research, high technology and higher education.

In an effort to account for the possible endogeneity of the share of college graduates in a city, we collected data on the year of opening of all colleges and universities in five of the six countries in our sample and we use driving distance to the nearest *historical* college or university as an instrumental variable for the share of college-educated residents in a city in the year of its country's manufacturing peak. We uncover evidence in support for the validity of the exclusion restriction. We do not have reliable data on college share for Japanese cities before 1980, so we do not include Japan in this part of the analysis.

We find that in the two decades before the relevant country's manufacturing peak, cities with a high share of college-educated workers experience a similar rate of employment growth as those with a low share of college-educated workers. Statistical tests fail to reject that the rate of growth for cities in the top quartile of their country's college share distribution is equal to the rate of growth for cities in the bottom quartile. The p-values for the periods between -1 and 0 and between -2 and -1 are 0.14 and 0.47, respectively.

By contrast, in the decades after the manufacturing peak, the employment trends diverge: cities with a high initial share of college-educated workers experience significantly faster employment growth. The divergence between cities with a high and low initial share of college graduates grows over time at an accelerating rate. We interpret these findings as evidence that in the period when manufacturing employment was still growing in the countries in our sample, the local share of college graduates was not an important driver of local employment growth, probably reflecting the fact that manufacturing plants at that time did not make intensive use of highly skilled workers. By contrast, in the period of de-industrialization, the local share of college graduates has become an increasingly im-

portant predictor of local employment growth, possibly reflecting a shift in employment among industrialized countries toward human capital-intensive industries.

We estimate that a city with a 1% higher initial share of college–educated residents experienced a 2.95 percent faster employment growth per decade in the years between its country's manufacturing peak and 2010, holding constant the initial share of manufacturing employment. Quantitatively, this is a large effect: it implies that a city with an initial college share one standard deviation above its country's median experienced a decadal growth of employment that was 9.1 percent faster.

We conclude our analysis by focusing on the effects by industry. We expect the employment effect of initial college share to be particularly pronounced for industries that are human capital intensive, since cities with a large skill base should be particularly attractive to employers who make intensive use of skills. While the industry classification in our data is coarse in the early years for most countries, the data for the UK and the US allow us to identify employment by two-digit industries for the entire period.

We find little evidence that a higher share of college-educated residents in a city is associated with smaller declines in manufacturing employment. By contrast, we uncover a positive effect on employment in Human Capital and Knowledge Intensive Services. As defined by Eurostat (2020a,b), this group includes services that make intensive use of highly educated workers. It includes, for example, Research and Development (NAICS 54); Education (NAICS 61); Financial Intermediation (NAICS 52); and Post and Telecommunication (NAICS 51). While in the years leading up to the manufacturing peak we find no association between the local share of college graduates and employment growth in this sector, after the manufacturing peak, we find a positive association. Our estimates indicate that a city with a 1% higher share of college-educated residents experienced a 4.3 percent faster employment growth per decade in Human Capital and Knowledge Intensive Services in the period of deindustrialization.

Taken together, our findings indicate that the negative labor demand shock caused by deindustrialization had different effects on local employment depending on the initial level of schooling of the local labor force. For former manufacturing hubs, the disappearance of factory jobs did not necessarily lead to total employment declines. A strong local human capital base was an important factor in successfully adapting to the negative shocks associated with manufacturing decline. In cities with an initially high share of college graduates, the loss of manufacturing employment was more than offset by gains in Human Capital and Knowledge Intensive Services. In terms of place–based policies for communities with a former manufacturing base, it would seem that investment in the education of local workers is an industrial policy with the potential to increase the probability of economic recovery.

Our analysis is related to previous studies on the relationship between changes in manufacturing employment and local economies. Examples include but are not limited to Au-

tor et al. (2013), Fort, Pierce, and Schott (2018), Charles et al. (2019), Gathmann, Helm, and Schönberg (2020), Hornbeck and Moretti (2021), and Hanson and Livas (2023). Our analysis is also related to Duranton (2007), who provides the microeconomic foundations for the geographical churning of industries, and Findeisen and Südekum (2008), who study spatial churning for German cities. Our findings on the effect of college share on subsequent employment changes are part of the broader literature on the relationship between human capital and local labor market outcomes and complement earlier work by Glaeser and Saiz (2004).[3] Finally, our analysis is related to the literature on the effect of universities on local economies (Valero and Van Reenen, 2019; Kantor and Whalley, 2014, 2019; Nimier-David, 2022). Within this literature, the papers that are closest to ours are the recent study by Howard, Weinstein, and Yang (2021) which compares U.S. counties that were assigned normal schools to counties that were assigned insane asylums to show that having a regional university helps to offset the negative effects of manufacturing decline; and a related paper by Andrews, Russell, and Yu (2023), which finds that US counties with a college have larger share of employment in high human capital sectors.[4]

The remainder of this paper is organized as follows. In Section 2 we describe the data. Our main empirical findings are presented in Sections 3 and 4. Section 5 concludes.

2 Data

We combine and harmonize data on employment, industry composition, schooling achievement of local workers, and location and opening date of college and universities for France, Germany, Japan, Italy, the United Kingdom and the United States. Our geographical unit of analysis is a Local Labor Market (LLM). The exact definition varies across countries, but in all six countries in our sample LLMs are defined based on residential and commuting patterns. Specifically, LLMs are defined to reflect an economic unit, rather than administrative boundaries. In each country the boundaries of a LLM are designed so that the majority of its residents live and work in the LLM. For example, in the case of New York, the LLM includes not just the city of New York, but also the surrounding suburbs where most commuters live. In urban settings, LLMs generally correspond to metropolitan areas. We have a total of 1,993 Local Labor Markets in our sample. In the paper, we use the term "local labor market" and "city" interchangeably.

[3] Our findings are generally consistent with Moretti (2004); Gennaioli, La Porta, De Silanes, and Shleifer (2014); Carneiro, Liu, and Salvanes (2018); and Feng and Xia (2021). See also Rosenthal and Ross (2015) and Sianesi and Van Reenen (2003).

[4] See also Andrews (2023); Howard and Weinstein (2022).

2.1 Data on Employment, Industry Composition and Education

Here we describe the data sources that we use to measure employment, industry composition, and schooling achievement by decade at the LLM level in each of the six countries.

France: Data on employment status, industry, and schooling achievement are from the Census of Population for the years 1968, 1975, 1982, 1990, 1999, 2011. The original data are at the individual level (sample size ranges from 2,487,778 in year 1968 to 20,541,337 in year 2011) and were aggregated to the municipal level by Insee;[5] we aggregate them to the local labor market level. The share of college graduates in a local labor market is defined as the share of active population aged 25-54 with a completed four-year college or university degree. Since data for 1970 are unavailable, we construct 1970 employment and college share in a local labor market by averaging 1968 and 1975 employment and college share, respectively. For 1980, 1990, 2000 and 2010 we use 1982, 1990, 1999, 2011, respectively.

The geographical unit of analysis is *Zones d'Emploi*. These are Local Labor Markets defined by the French National Statistical Office (INSEE) and consist of aggregations of French municipalities based on commuting data. The procedure employed to define *Zones d'Emploi* is described in detail in Ronsac (1994). We use the 1984 definition of *Zones d'Emploi*.

Germany: Data on employment status, industry, and education are from the Establishment History Panel (BHP). The original data are at the individual level (sample size ranges from 19,353,380 employees in year 1975 to 23,242,278 in 2010) and were aggregated to the local labor market level by the Institute for Employment Research (IAB). To increase precision, we estimate employment in each decade in each LLM by taking a 3-year average around the relevant year. For instance, to estimate employment in 1990 in a given LLM, we take the average of employment in 1989, 1990 and 1991 in the relevant LLM. Industry figures are available at the 2-digits level. We estimate employment by 2-digits industry and LLM by averaging data across 3-year intervals. Since the industry classification changes between 1975 and 2010, we harmonize it using the crosswalk proposed by Eberle et al. (2011). The share of college graduates in a local labor market is defined as the share of employees in the BHP with a completed academic degree ("University" degree or "Technical College" degree).

Local Labor Markets are defined as *Arbeitsmarktregionen*, which are aggregations of German districts. The classification and aggregation procedure is described in detail in Kosfeld and Werner (2012). We use the 1984 geographical definition of *Arbeitsmarktregionen*.

We base our analysis on Local Labor Markets located in West Germany. Comparable data at the local labor market level for the territory of the former East Germany are

[5]For a description of the samples see https://international.ipums.org/international-action/sample_details/country/fr

available only from 1990 onwards. For brevity, throughout the paper, we refer to West Germany as Germany.

Italy: Data on employment at the municipal $\times$ industry level are from the Service and Manufacturing Census for the years 1961, 1971, 1981, 1991, 2001, 2011. The original data are at the individual level (sample size ranges from 9,463,457 in year 1961 to 16,424,086 in 2011) and were aggregated to the municipal level by the National Institute of Statistics (ISTAT). For each decade, we use the Census year that is closest to 1960, 1970, etc. For example, 1960 employment is measured using the 1961 Census; 1970 employment is measured using the 1971 Census; and so on. The share of college graduates in a local labor market is defined as the share of residents of a local labor market with a completed four-year college or university degree. Data on schooling achievement are from the Census of Population for the year 1981 (sample size: 56,556,911) and were aggregated to the municipal level by ISTAT.

The geographical unit of analysis is *Sistemi Locali Del Lavoro*. They are Local Labor Markets defined by ISTAT as aggregations of Italian municipalities, based on commuting data. The classification and aggregation procedure is described in Sforzi (1997). We use the 1981 definition of *Sistemi Locali Del Lavoro*.

Japan: We use data on employment status and industry from the Census of Population for the years 1970, 1980, 1990, 2000, 2010. The original data are at the individual level (sample size ranges from 104,665,171 in year 1970 to 128,057,352 in year 2010) and were aggregated to the municipal level by Sachiko Kazekami (Keio University). We were unable to find systematic high-quality data on college share for Japanese LLMs before 2000, so we do not include Japan in the part of the analysis that focuses on education.

The geographical unit of analysis is a Metropolitan Employment Area (MEA). MEAs are Local Labor Markets defined according to the classification proposed in Kanemoto and Tokuoka (2002) and include both the urban core of metropolitan areas and the surrounding suburban areas. We use the 1980 definition.

United Kingdom: We use individual level employment data from the Business Register and Employment Survey (sample size ranges from 18,299,130 in year 1976 to 17,929,166 in 2008). The data cover England, Wales and Scotland. Data for Northern Ireland are not available, and therefore this region is not included in the analysis. For brevity, throughout the paper, we refer to England, Wales and Scotland as United Kingdom .

To increase precision, we estimate employment in each decade in each LLM by taking a 3 year average around the relevant year, like we do for Germany. Industry figures are available at the 2-digits level. A time consistent industry classification between 1975 and 2010 is provided by the Office for National Statistics (ONS).

Information on schooling achievement is from the ONS Official Labor Market Statistics. College share is defined as the share of individuals in the LLM with a completed four-year college or university degree or professional vocational qualifications. Data are

available at the LLM level for 1981, 1991, 2001 and 2011. For 1971 they are available at the ward level. To assign ward level population counts to LLMs we created a weighting scheme based on the lowest geographical building block, namely Enumeration Districts (ED). We calculated the share of a ward that is contained in an LLM as the number of EDs for a given ward contained in that LLM divided by the total number of EDs in the ward. We use this indicator to estimate the number of workers with a college degree in each LLM.

The geographical unit of analysis is based on *Travel to Work Areas*, which are aggregations of British wards (in England and Wales) or postcode sectors (in Scotland), based on commuting data. The classification and aggregation procedure is described in Department of Employment (1984) and Coombes, Green, and Openshaw (1986).[6] We use the 1984 definition of *Travel to Work Areas*.

United States: We use data on employment by county and industry from the County Business Patterns for 1956, 1964, 1970-71, 1977-78, 1987-88, 1996-97, 2006-07 and 2012. The main strength of the CBP is the fact that data are available for as far back as 1956 at a fine geographical-industry detail.[7] Data on worker education and other characteristics are from the Census of Population for 1960, 1970, 1980, 1990, 2000 and 2010. The college share in each local labor market is defined as the share of workers living in a local labor market with a completed four-year college degree.

As a geographical unit of analysis we use the Metropolitan Statistical Areas (MSA). Data on employment at county-industry level are aggregated to the MSA-industry level. MSAs are defined by the US Census based on commuting patterns to include Local Labor Markets where most workers live and work. We use the 1990 definition and we include in our analysis only MSAs that are consistently defined in the sample period.

2.2 Data on Colleges and Universities

In addition to data on employment, industry mix and education, we gathered data on the location of historical four-year colleges and universities in five of the six countries in our sample. Specifically, we put together and harmonized data on the exact location and year of opening of each institution of higher education that exists in 2010 in France, Germany, Italy, the UK and the US. For France, Germany, Italy and the UK, the data on location and opening date come from the European Tertiary Education Register (ETER), which provides information on Higher Education Institutions (HEIs) in Europe. For the US, we use the data collected by Currie and Moretti (2003) reporting the address and opening date of all two- and four-year colleges in the country. For consistency with the European data, in the US we use only four-year colleges. Since we were unable to find historical

[6] Duranton and Overman (2008) provide a detailed spatial analysis of the UK manufacturing sector.

[7] We are grateful to Gilles Duranton for making the 1956 data available.

data on college share by local labor market for Japan, we do not include Japan in the part of the analysis that uses the information on the location and date of openings of colleges and universities.

In our analysis, we use distance to the nearest historical college or university as an instrumental variable for the share of college-educated workers, where historical colleges or universities are defined as colleges or universities that existed 20 years before the period of analysis. In some specifications, we use colleges or universities that existed 30, 40 or 50 years before the period of analysis. For every institution of higher education and Local Labor Market pair within each country, we calculate the driving distance from the institution's address to the centroid of the Local Labor Market. In our analysis, we only consider distance between institutions and LLMs in the same country, since historically most students attended colleges or universities in their own country. To measure driving distance, we use open Street Map data from GeoFabrik (https://www.geofabrik.de/). We assume that driving distance has not changed over time in significant ways, so that distance measured today is a good proxy for distance at the beginning of the period of analysis.

2.3 Manufacturing Peaks and Summary Statistics

Figure 1 shows the level of total manufacturing employment by decade in the six countries under study: France, Germany, Italy, Japan, United Kingdom, the United States. To make the magnitude of the changes comparable across countries, we normalize manufacturing employment to 1 in each country's peak year. The figure shows that manufacturing employment peaked at a different point in time in different countries. In the United Kingdom and United States it peaked in 1970; in France and Italy in 1980; in Germany and Japan in 1990.[8]

Throughout the paper, we measure the city-level mean decadal percent change in employment as the difference in log employment between the year of a country's manufacturing peak and 2010 divided by the number of decades between the peak and 2010. We use this normalization because manufacturing employment peaks in different years in different countries. For example, since for the US and the UK the peak is in 1970, the mean decadal percent change in employment is the difference in log employment between 1970 and 2010 divided by 4: $\Delta \ln(Y_{lc(l)}) = \frac{\ln(Y_{lc(l)2010}) - \ln(Y_{lc(l)1970})}{4}$, where $Y_{lc(l)2010}$ is employment in local labor market l located in country $c(l)$ in year 2010 and $Y_{lc(l)1970}$ is l's employment in year 1970. For France and Italy, where the peak is 1980, the mean decadal percent change in employment is the difference in log employment between 1980 and 2010, divided by 3: $\Delta \ln(Y_{lc(l)}) = \frac{\ln(Y_{lc(l)2010}) - \ln(Y_{lc(l)1980})}{3}$. For Germany and Japan

[8]To create the series for the UK used in this Figure, we use data from FRED at the St. Louis Fed for 1960, 1970, 1980, 1990, 2000 and 2010 because our micro data on employment for the UK don't go back to 1960. For all other countries, this figure is based on the data that we use in the rest of the analysis.

it is calculated over 2 decades: $\Delta \ln(Y_{lc(l)}) = \frac{\ln(Y_{lc(l)2010}) - \ln(Y_{lc(l)1990})}{2}$. For a given local labor market, the mean decadal growth rate of employment measures the percent change in employment experienced by that labor market on average *per decade* in the decades following the country's manufacturing peak.

Summary statistics for the pooled sample that includes all six countries are in Table 1. The first row shows that the average local labor market experiences a mean growth rate in total employment of 7.5 percent per decade in the decades between the relevant country manufacturing peak and 2010. The second row shows the corresponding figure for manufacturing employment. The average local labor market experiences a mean growth rate in manufacturing employment of -7.0 percent per decade in the decades between the relevant country manufacturing peak and 2010. Thus, while the average local labor market in our six countries experienced an increase in the total number of jobs, it experienced a contraction in the total number of manufacturing jobs.

The third row shows that in the year of the relevant country manufacturing peak, 35.5% of workers in the average local labor market in the sample were employed in the manufacturing sector. The fourth raw reports mean total employment to give a sense of the magnitude of the typical local labor market in the sample. The fifth row indicates that in the average local labor market the share of workers with a college or university degree was 4.3% in the year of the relevant country manufacturing peak.

The table also indicates that in the year of manufacturing peak, 11.6% and 5.4% of workers in the average local labor market were employed in Human Capital and Knowledge Intensive Services or in High Tech manufacturing, respectively. Eurostat classifies services as Human Capital and Knowledge Intensive Services based on the share of tertiary educated persons at NACE 2-digit level (Eurostat, 2020a; Eurostat, 2020b). This group includes a diverse set of industries—for example: Research and Development; Education; Financial intermediation; and Post and Telecommunication—that make intensive use of highly educated workers. Only in the UK and the US are the industry identifiers in our micro data fine enough to allow us to identify Human Capital and Knowledge Intensive Services. Thus, the sample size for this variable is significantly smaller. Eurostat classifies manufacturing industries as High Tech based on R&D intensities (Eurostat, 2020a; Eurostat, 2020b). For France the industry identifiers in our micro data are not fine enough to allow us to identify High Tech manufacturing.[9] The last row in the table

[9]These are the industries that Eurostat classifies as Human Capital and Knowledge Intensive Services (the numbers indicate NACE Rev 1.1 codes): 61 Water transport; 62 Air transport; 64 Post and telecommunications; 65 Financial intermediation; 66 Insurance and pension funding; 67 Activities auxiliary to financial intermediation; 70 Real estate; 71 Renting of machinery and equipment without operator and of personal and household goods; 72 Computer and related activities; 73 Research and development; 74 Other business activities; 80 Education; 85 Health and social work; 92 Recreational, cultural and sporting activities. These are the industries that Eurostat classifies as High Tech manufacturing: 24.4 Manufacture of pharmaceuticals, medicinal chemicals and botanical products; 30 Manufacture of office machinery and computers; 32 Manufacture of radio, television and communication equipment and apparatus; 33 Manufacture of medical, precision and optical instruments, watches and clocks; 35.3 Manufacture of aircraft and

reports the mean distance to the nearest historical college or university, where distance is measured to the nearest college or university that existed 20 years before the relevant country manufacturing peak.

Summary statistics by country are in Table 2. The first row shows that there is wide variation across countries in the mean growth rate in total employment per decade in the decades after the relevant country manufacturing peak. The second row shows that in all six countries, the mean growth rate in manufacturing employment per decade in the decades after the relevant country manufacturing peak was negative, consistent with Figure 1. The entries on total employment in the year of manufacturing peak indicate that based on the definition of Local Labor Markets that we adopted, Local Labor Markets in Japan, the US and Germany are the largest, while Local Labor Markets in Italy are the smallest, with Local Labor Markets in France and the UK in the middle.

Figure 2 shows the distribution of the share of employment in manufacturing across local labor markets in each country in the year of the country's manufacturing peak. The figure shows that in all six countries in our sample there is wide dispersion across Local Labor Markets in the manufacturing share. The standard deviation in manufacturing share across local labor markets is largest in Italy (std. dev. 0.18) and the US (std. dev. 0.16), indicating that the spatial distribution of manufacturing employment was most uneven in these two countries. This likely reflects the fact that in Italy and the US manufacturing was historically geographically concentrated in some regions, and largely absent in the South of each country. By contrast, the standard deviation is smallest in Germany (std. dev. 0.09) and Japan (std. dev. 0.10), indicating that the geographical distribution of manufacturing was relatively more uniform there.

3 Heterogeneity in Employment Growth During the Period of De-Industrialization

3.1 Initial Manufacturing Share

Figure 1 above has highlighted the overall decline of manufacturing employment in the six countries in our sample. Since manufacturing employment was not evenly distributed across cities within each of the six countries (Figure 2), the effects of deindustrialization on local economies are unlikely to be homogeneous across cities. Cities with a strong manufacturing presence at the beginning of the period were presumably more exposed to the negative effects of deindustrialization than cities with a weaker manufacturing presence. Specifically, during the period of deindustrialization, Local Labor Markets on the right side of the distribution in Figure 2 presumably experienced a more negative shock

spacecraft.

to labor demand and therefore slower employment growth than those on the left side of the distribution.

This is illustrated in Figure 3a, which shows the change in total employment in the two decades before and the four decades after the relevant country's manufacturing peak. Local Labor Markets are divided into three groups based on the local share of manufacturing employment measured in the year of manufacturing peak. Thus "Top Tercile" includes the Local Labor Markets that in the year of their country's manufacturing peak had a share of manufacturing employment in the top tercile of their country's distribution. The "Middle Tercile" and "Bottom Tercile" are defined similarly. In the rest of the paper, we will refer to Local Labor Markets belonging to the Top Tercile as "former manufacturing hubs", since in the year of their country's manufacturing peak they had a high share of employment in manufacturing compared to the rest of their country.

Time $t = 0$ on the x-axis represents the year of the manufacturing peak. The Figure reports the percent difference between total employment in a given decade and total employment at $t = 0$. Since there are significant differences across countries in their overall rate of employment growth, for ease of comparison, the change in employment for a given city is computed in deviation from its country's mean. This removes country-level differences in aggregate growth from the Figure. An entry of 0.1 for a given city at time t, for instance, means that between 0 and t employment in that city has grown by 10%, over and above its country's mean employment growth in the same period.

Throughout the paper, we focus on relative city growth—as opposed to absolute growth—because the six countries experienced different increases in total population and total employment in our sample period. For our purposes, the rate of growth of a city relative to its country mean is more informative than its absolute rate of growth. For example, a city with a 10% growth in employment in a country with a 20% overall employment growth has arguably a weaker local labor market than a city with a 10% growth in employment in a country with a 5% overall employment growth.

The Figure shows that in the two decades before the manufacturing peak, employment in cities belonging to the three groups grows at a similar pace (relative to aggregate employment in their respective countries).[10] In the decades after the manufacturing peak, the three lines diverge at an accelerating rate: Employment in former manufacturing hubs declines (relative to aggregate employment in their respective countries). By contrast, relative employment in cities in the other two terciles increases, with relative employment in the bottom tercile—which includes cities with the smallest initial share of manufacturing employment—increasing the most.[11]

[10]This is notable because it means that in this period–in which manufacturing employment is still growing–cities with a large manufacturing sector are not growing any faster than cities with a small manufacturing sector.

[11]This Figure uses all the cities in our sample and all the available years. It is based on an unbalanced panel due to the fact that the year of manufacturing peak varies across countries and the period for which

Figure 3b shows the corresponding trends by country. The relative decline of the Top Tercile is clearest in France, the UK and the US. In Italy and Japan, the Top and Middle Terciles appear to have comparable changes in relative employment by 2010, with the Bottom Tercile outperforming the other two. The picture for Germany in the decades before the country's manufacturing peak points to a faster growth of the Top Tercile, and a slower growth of the Bottom Tercile. Since the country's manufacturing peak, the rates of relative growth of the three Terciles appear to have converged. Thus, relative to its pre-trends the Top Tercile in Germany has experienced a slowdown in growth compared to the other two terciles.

Figures 4a and 4b show more explicitly the relationship between total employment growth in the decades after the manufacturing peak and the initial manufacturing share. In particular, Figure 4a presents a binned scatter plot of the city-level mean decadal growth rate of total employment between the year of manufacturing peak and 2010 as a function of the city's manufacturing share in the year of the country's peak. It includes all the cities in our sample. Figure 4b presents the same relationship by country.

The two figures show a clear negative correlation between the two variables, confirming that Local Labor Markets where manufacturing accounted for a large share of employment in the year of manufacturing peak experienced a larger decline in total employment after the peak (relative to their country average) than Local Labor Markets where manufacturing accounted for a small share of employment. This is consistent with Figures 3a and 3b.

A pooled regression using all the cities in the six countries with country fixed effects yields a slope of -0.169 (0.016). This estimate implies that a 1 standard deviation increase in initial manufacturing share (16.1 percentage points) is associated with a decadal growth in total employment in the following decades that is 2.71 percent slower (relative to their country average). This effect is economically large: it amounts to 36% of the mean decadal growth in total employment experienced by the average city in the sample (reported in Table 1). In country-specific regressions, the coefficients on initial manufacturing share for France, Germany, Great Britain, Italy, Japan and the United States are, respectively: -0.27 (0.03); -0.09 (0.06); -0.30 (0.04) ; -0.10 (0.02); -0.11 (0.15); and -0.37 (0.09).

The negative slopes in Figures 4a and 4b likely reflect a combination of effects. First and foremost, they reflect the employment losses directly stemming from the decline of manufacturing jobs. Second, they probably reflect additional employment losses caused by de-agglomeration effects. For example, Gathmann et al. (2020) focus on mass layoffs and find that affected regions lose many more jobs than in the initial layoff. Additionally,

we have employment data also varies across countries. The employment changes of the three groups do not mechanically sum up to 0 in each period because of the different city sizes and the unbalanced nature of the sample.

employment outside manufacturing could decline due to lower demand for local non-traded services. As factories close in a city, demand for locally provided non–traded services—construction, retail, restaurant, etc—also declines due to a job multiplier effect. The loss of construction jobs is particularly damaging. In Rust Belt communities in the US, for example, construction jobs traditionally represented the best-paying jobs outside of manufacturing for workers without a college degree.[12] Finally, it's in principle possible that there are offsetting general equilibrium effects. For example, it is possible that lower wages and lower real estate costs may attract outside investment, potentially offsetting part of the direct employment losses.

3.2 Former Manufacturing Hubs

The findings in Figures 4a and 4b are intuitive and consistent with the existing literature (Autor et al., 2013; Charles et al., 2019; Rice and Venables, 2020; Hanson and Livas, 2023).[13] They indicate that on average, cities with a higher manufacturing share in the peak year experienced a steeper decline in overall employment in the decades after the peak year. But this average effect can potentially mask a significant amount of spatial heterogeneity. The amount of heterogeneity that exists in the employment effects of deindustrialization across cities with similar initial shares of manufacturing employment has received less attention in the literature.

Figures 5a and 5b show the distribution across cities of total employment changes in the decades following each country's manufacturing peak expressed in deviation from the country mean. In Figure 5a, all countries are pooled together, while Figure 5b shows the corresponding distribution by country. The figures include only "former manufacturing hubs". Presumably, cities in this group are the most exposed to the consequences of the manufacturing decline.

Cities to the left of 0 are manufacturing hubs that in the period between their country manufacturing peak and 2010 have lost employment (relative to their country mean), while cities to the right of 0 are manufacturing hubs that in the same period have gained employment (relative to their country mean). Thus cities on the right of 0 are former manufacturing hubs whose total employment has fully recovered from the manufacturing

[12] Using US data, Moretti (2010) estimates that for each manufacturing job lost in a city, 1.6 additional jobs are eventually lost in the non-traded sector in the same city, although the size of the multiplier effect appears to be smaller in European countries (Moretti and Thulin, 2013; Van Dijk, 2014).

[13] Glaeser (2009) regresses the 1950-1980 log change in city population on initial specialization of the city in manufacturing and finds a negative correlation. The estimated coefficient indicates that on average, a city with 10% more manufacturing employment in 1950 experienced a 18% larger population loss between 1950 and 1980. Charles et al. (2019) find that manufacturing decline in a local area had large and persistent negative effects on local employment rates, hours worked and wages. Rice and Venables (2020) find largely persistent effects of 1970's negative economic shocks on UK cities. Hornbeck and Moretti (2021) find that increases (declines) in labor demand in manufacturing in a city cause increases (declines) in the city's total employment. See also Fort et al. (2018) for an analysis of broader regional differences.

losses and even exceeded their country mean growth rate. It is clear from Figures 5a and 5b that the magnitude of total employment changes experienced by former manufacturing hubs varies significantly across cities within each country in the period of manufacturing decline. In all countries there is more mass to the left of 0, since on average manufacturing hubs have lost employment relative to the country mean. However, a sizable fraction of the distribution is above 0, indicating that a significant number of manufacturing hubs fully recovered or grew faster than the country average in the years after the manufacturing peak.[14]

Column 1 in Table 3 quantifies the share of manufacturing hubs in each country with full recovery, defined as having a mean rate of decadal employment growth that is equal to or above the relevant country mean. This share corresponds to the area of the distribution above 0 in Figures 5a and 5b. The first row shows that the average share in the 6 countries combined is 0.34. This share is surprisingly high. It points to a fast employment growth in a group of cities that, by definition, started off with a large share of employment concentrated in manufacturing during a period when aggregate manufacturing employment was shrinking. Despite the fact that these cities experienced a significant negative labor demand shock in the form of loss of manufacturing employment, in more than a third of cases their total employment grew faster than the rest of the cities in their respective country. The share of former manufacturing hubs with positive relative growth is economically large in all countries. It ranges from 0.17 in the US and 0.28 in the the UK, to 0.47 in the Germany, with Italy, Japan and France in the middle.

Columns 2 to 4 quantify the amount of spatial heterogeneity in employment growth within each country in the years after the peak among former manufacturing hubs measured by the difference between the 90th and the 10th percentile of employment growth in the decades following the country's manufacturing peak (column 2); the interquartile range (column 3); and the standard deviation (column 4). The table shows significant differences in labor market performance across communities within each country. For example, the 90-10 percentile difference ranges from 15.9 percentage points in France to 23.4 percentage points in the US. The interquartile range varies from 7.9 percentage points in Germany to 13 percentage points in the UK.

These findings are based on the group of cities that in the year of their country manufacturing peak had a local manufacturing employment share in the top tercile of their country distribution. The share of cities that experience a rate of decadal employment growth equal to or above the relevant country mean remains high if we use more stringent criteria to define former manufacturing hubs. Table 4 re-estimates the share when we define former manufacturing hubs as Local Labor Markets that in the year of their country manufacturing peak have a manufacturing employment share in the top quartile of the

[14]For completeness, Appendix Figure A.1 show the distribution of the mean decadal growth rate for all cities, not just manufacturing hubs.

country distribution (column 2); or in the top 10% of their country distribution (column 3). The shares of manufacturing hubs with growth faster than the rest of their country decline slightly as we move from column 1 to column 3, but remain economically large.

For each country, Table 5 illustrates examples of former manufacturing hubs with an similar initial manufacturing share that experienced relative decline or recovery. In Italy, for example, Udine and Padua had a similar share of manufacturing employment in 1980, the peak year for the country's manufacturing employment: 0.43 and 0.44, respectively. They are both located in the North-East, less than 100 miles apart. But in the 3 decades after 1980, they experienced vastly different rates of employment growth. Udine employment declined on average by 3% per decade (in deviation from Italy's mean). By contrast, Padua employment grew on average 7% per decade (in deviation from Italy's mean), significantly outperforming the rest of the country despite the employment losses associated with the decline in manufacturing employment. Padua is home to one of the oldest and most established Italian universities.

In Germany, Wuppertal and Erlangen had, respectively, 46% and 47% manufacturing share in 1990. But since then Wuppertal lost 14% of employment per decade compared to the German mean, while Erlangen gained 7% per decade compared to the German mean. In the UK, Middlesbrough and Slough had 44% of manufacturing employment in 1970. But their experience was vastly different in the 4 decades following the peak, with Middlesbrough employment declining by 17% per decade (relative to the UK mean) and Slough employment growing by 8% per decade (relative to the UK mean). In the US, Columbus and Toledo are both located in Ohio and in 1970 had a comparable manufacturing share: 35% vs 39%. Since then, Toledo employment has declined on average 13% per decade (relative to the US mean), while Columbus employment has grown on average 1% by decade (relative to the US mean). Columbus is the home of the Ohio State University—the flagship institution in the state.

4 The Effect of the Initial Share of College-Educated Workers on Employment Growth During the Period of De-Industrialization

Overall, the findings in the previous Section point to a highly heterogeneous effect of deindustrialization on localities in the six countries in our analysis. Cities with an initially similar manufacturing share had vastly different labor market experiences. While *on average* total employment growth declined with the initial local manufacturing share–as indicated by the regression lines in Figures 4a and 4b–this average decline masks large differences across localities. Some former manufacturing hubs experienced relative employment declines even steeper than the declines predicted by the regression line in Fig-

ures 4a and 4b, while others fully recovered and even surpassed their relative employment at the peak.

The obvious question is what factors may explain the difference across Local Labor Markets in their propensity to recover from to the negative labor demand shock created by the decline of manufacturing. In this section, we focus on the role played by the initial level of human capital of local residents, measured by the share of residents with a college or university degree in the year of the manufacturing peak. We ask whether initial differences in the share of college educated workers across Local Labor Markets are systematically associated with their subsequent employment growth during the years of manufacturing decline. Local Labor Markets with a better-educated labor force may be better positioned to recover from deindustrialization if a better-educated labor force attracts new employers outside manufacturing, offsetting the employment losses in manufacturing.

A concrete example is Pittsburgh, which transformed itself from a declining local economy dominated by heavy manufacturing in the 1970s into a innovation-driven local economy in more recent years. The collapse of the steel, railroad and mining employment in the 1970s and 1980s resulted in the loss of a third of its population. But Pittsburgh had a strong human capital base and important research institutions like Carnegie Mellon University and the University of Pittsburgh. After the decline of manufacturing employment, the city's skill base enabled Pittsburgh to transition from heavy manufacturing to an "eds and meds" economy (Andes et al., 2017; Mills et al., 2022). Today, the Pittsburgh region's dominant industries are human capital-intensive sectors, such as medical research, green technology and higher education. Pittsburgh also developed industry clusters around advanced technologies like robotics and attracted employers like Google, Amazon, Apple, and Uber. The region's per capita R&D spending is nearly two and a half times the U.S. average (Andes et al., 2017). Nationwide, these industries' employment and payroll have expanded significantly over the past 50 years. Pittsburgh's skill base allowed the city to capture part of this growth, offsetting the losses of manufacturing employment and payroll.

Of course, it's difficult to generalize based on one data point. Pittsburgh is not a typical former manufacturing hub, Carnegie Mellon is not the average university and idiosyncratic state economic policies may have played a role in the city's recovery (Armstrong, 2021). Thus, it is an open question whether Pittsburgh's economic recovery is an exception, or whether it is representative of the experience of other cities in industrialized economies.[15]

[15] Another prominent example is Boston. In the 1960s and 1970s, Boston was a declining city with a high share of manufacturing employment and a falling population. But Boston had a strong skill base due to the presence of its many colleges and universities. This skill base "enabled Boston to become a successful city in the information age" (Glaeser, 2005). Today, the city's main industries are, like Pittsburgh's, human capital-intensive sectors: biotech, high tech, and financial services. However, Boston is probably even less

While the main channel that we have in mind is that a better-educated labor force causes an increase in *labor demand* stemming from growth in human capital-intensive industries, we don't rule out other channels. An initially higher level of human capital in a local labor market may result in faster employment growth due to more *labor supply* to that labor market. For example, a better-educated labor force may result in improvements in local amenities – school quality, safety, restaurants, entertainment, cultural amenities, etc. – which in turn make the city endogenously more attractive to other educated workers, as demonstrated by Diamond (2016). Of course, increases in labor demand and labor supply are not mutually exclusive. Our objective here is to estimate the *overall* effect of the initial level of human capital in a local labor market in the peak year of manufacturing on subsequent employment growth. Disentangling what fraction of the overall employment effect is due to demand or supply is behind the scope of this paper.

Our focus on the share of college-educated workers does not imply that human capital of the labor force is to be considered the only possible explanation of the geographical variation uncovered in the previous section. It is certainly possible that other factors played a role. Our analysis is to be considered as a first step in understanding the determinants of geographical differences in employment growth in the years of manufacturing employment decline in industrialized countries.

4.1 Graphical Evidence

Figure 6 shows the evolution of total employment in the two decades before and the four decades after the relevant country's manufacturing peak in cities with a high and low share of college-educated residents. We divide Local Labor Markets based on the country-specific quartile of the share of residents with a college degree in the year of manufacturing peak. The top group, for example, includes Local Labor Markets with an initial share of college-educated workers in the top quartile of their country's distribution. The Figure is based on data from France, Germany, Great Britain, Italy, and the United States. Recall that Japan is excluded from this part of the analysis because data on the share of college-educated workers are not available for Japan at the local level for early years.[16]

The Figure shows that before the manufacturing peak, Local Labor Markets with a high share of college-educated workers experience a similar rate of employment growth as those with a low share of college-educated workers. Between -1 and 0 (i.e. in the decade before the manufacturing peak) the four quartiles appear to have trends that are

representative than Pittsburgh. Even at the bottom of its economic decline in the mid-1980s, it never reached the levels of economic malaise experienced by cities like Detroit, Liverpool or Duisburg. The presence of Harvard, MIT, and many other top research universities as well as premier research hospitals is unparalleled among metro areas in industrialized countries.

[16] As before, employment is normalized to 1 in the year of the relevant country's manufacturing peak. The change in employment for a given city is computed in deviation from its country's mean.

largely indistinguishable. Between -2 and -1 (i.e. two decades before the peak) Local Labor Markets in the top quartile experience a slightly *less* steep employment growth. Statistical tests fail to reject that the rate of growth for cities in the top quartile of their country's college share distribution is equal to the rate of growth for cities in the bottom quartile. The p-values for the periods between -1 and 0 and between -2 and -1 are 0.14 and 0.47, respectively.

In the decades after each country's manufacturing peak, the employment trends diverge. Local Labor Markets in the top quartile experience the fastest employment growth, while Local Labor Markets in the bottom quartile experience the slowest employment growth. Local Labor Markets in the second and third quartile are in the middle, with the second quartile exhibiting a slightly steeper slope than the third quartile. The divergence between the top and the bottom quartiles appears to grow over time at an accelerating rate.

Figure 7 shows more explicitly the correlation between college share and employment growth. It plots the college share in the year of the manufacturing peak on the x-axis and the percent decadal employment change on the y-axis (both expressed in deviation from country-level means), controlling for the share of manufacturing at the peak. In the top panel, the percent decadal employment change is measured before the manufacturing peak (in the two decades preceding the relevant country's manufacturing peak, i.e. the period between $t = -2$ and $t = 0$); in the bottom panel, employment growth is measured after the manufacturing peak (in the period between the country's manufacturing peak and 2010). The top panel confirms the lack of a positive relationship before the manufacturing peak. The slope is negative (-0.685 (0.478)) and it is not statistically different from 0. By contrast, the bottom panel shows the positive relationship, confirming that cities with an initially high college share experienced faster employment growth in the period of deindustrialization compared to cities in the same country with an initially low college share.

We interpret these findings as evidence that in the period when manufacturing employment was still growing in the countries in our sample, the local college share was not correlated with employment growth, possibly reflecting the fact that manufacturing plants at that time did not make intensive use of highly skilled workers. By contrast, in the decades since the manufacturing peak, the initial college share becomes increasingly predictive of employment growth, possibly reflecting a shift in employment among industrialized countries toward human capital-intensive sectors.

Figure 8 shows the evolution of employment in one such sector: Human Capital and Knowledge Intensive Services, as defined by Eurostat (2020a,b). These are service industries that, by definition, make intensive use of human capital (see Section 2.3 for the exact definition). The geographical location of firms in this group of industries is expected to be particularly sensitive to the availability of college-educated workers in a Local Labor Market, as in the case of Pittsburgh discussed above. The Figure is based on a sample that

includes only Local Labor Markets in the US and UK because the level of industry detail in other countries is too coarse for us to identify Human Capital and Knowledge Intensive Services.

The Figure indicates that Local Labor Markets with a high and low share of college graduates have similar pre-trends in the decade before the relevant manufacturing peak. A statistical test fails to reject that the slopes for the top and bottom quartiles are equal in the period between -1 and 0 (p-value 0.40).

In the decades after the relevant manufacturing peak, employment in Local Labor Markets in the top quartile grows faster than employment in Local Labor Markets in the bottom quartile. This figure is consistent with the notion that in the decades after each country's manufacturing peak, Local Labor Markets endowed with more skilled residents attracted a larger share of employment in Human Capital and Knowledge Intensive Services. Thus employment growth in this part of the service sector appears to be one possible channel through which the initial level of education of local workers affected subsequent total employment growth.

4.2 Empirical Specification

We quantify the effect of a higher initial share of college graduates on employment growth by relating the percent change in employment in local labor market l located in country $c(l)$ between the year of country $c(l)$'s manufacturing peak and 2010, to the initial share of l's residents who have a college or university degree, holding constant the initial share of manufacturing and other local characteristics:

$$\Delta \ln(Y_{lc(l)}) = \beta_h \textit{College Share}_{lc(l)} + \beta_m \textit{Manuf Share}_{lc(l)} + \gamma X_{lc(l)} + \alpha_{c(l)} + u_{lc(l)} \quad (1)$$

where $\Delta \ln(Y_{lc(l)})$ is the mean decadal percent change of total employment or employment by sector; *College Share*$_{lc(l)}$ and *Manuf Share*$_{lc(l)}$ are the share of l's residents with at least a college or university degree and the share of l's employment in manufacturing, respectively, both measured in the year of $c(l)$'s manufacturing peak; $X_{lc(l)}$ is a vector of additional local labor market-level characteristics in the year of $c(l)$'s manufacturing peak; and $\alpha_{c(l)}$ is a vector of country fixed effects that absorb country-specific employment shocks taking place between the country manufacturing peak and 2010. For example, if France's economic growth between 1990 and 2010 is higher than Italy's, the country dummies absorb this difference. The country effects also account for the fact that $\Delta \ln(Y_{lc(l)})$ is computed for different countries over different time periods. For example, aggregate employment growth in the period 1970-2010 does not need to be the same as the one in the period 1980-2010. The residual $u_{lc(l)}$ represents shocks to l's employment taking place between the year of manufacturing peak and 2010, caused by shifts in the

unobserved determinants of labor demand in l or labor supply to l.

The coefficient β_h captures the reduced form relationship between the level of human capital in a local labor market in the peak year of manufacturing and subsequent employment growth. As discussed above, it reflects both the effect of labor demand shifts—a better-educated labor force in the year of manufacturing peak attracts more firms in human capital-intensive industries in the subsequent years—and labor supply shifts—a better-educated labor force results in better endogenous local amenities, which in turn attract more skilled workers.

4.2.1 Proximity to Colleges or Universities

Estimates of β_h in Equation 1 are identified by comparing the rate of growth of employment of cities with high and low initial share of college-educated workers within each country. The concern in interpreting estimates of the coefficient β_h is that, after conditioning on the initial share of manufacturing employment, the initial share of college graduates in a city may be correlated with time-varying unobserved factors that systematically affect changes in local labor demand or supply–and ultimately changes in the level of employment–during the period of deindustrialization: $Corr(\textit{College Share}_{lc(l)}, u_{lc(l)}) \neq 0$.

In this respect, a specific concern is that in the years leading up to the country's manufacturing peak, college-educated workers move to cities where the local economy is expected to grow faster than the rest of the country. This would be a case of reverse causality: expected future employment growth attracts highly educated residents, rather than the presence of highly educated residents raises future growth, causing OLS estimates of β_h to be upward biased.

Figure 6 does not appear to be particularly consistent with this possibility. Specifically, it does not seem to be the case that employment in Local Labor Markets with a high share of college-educated workers is growing significantly faster in the two decades leading up to the relevant country's manufacturing peak compared to Local Labor Markets with a low share of college-educated workers.

To allay concerns about reverse causality and omitted variables, we instrument $\textit{College Share}_{lc(l)}$ with the driving distance between *l* and the nearest historical college or university. Proximity to colleges or universities increases the supply of college graduates to a Local Labor Market (Goldin and Katz, 1999) and has been used as an instrumental variable for the number or the share of college-educated individuals in a locality in previous studies (for example: Card (1993, 2001); Moretti (2004); Andrews (2023)).[17] Unlike most previous

[17]Proximity to college and universities increases the number of college graduates in an area by increasing the probability that local residents enroll in college and by attracting college-educated workers from outside the area. In addition, Howard et al. (2021) show that college and universities directly increase the number of local college graduates by employing college-educated workers. Andrews et al. (2023) find that in their context, the benefits of college proximity are not primarily driven by college employees or in-migration.

studies, we use college proximity as an instrument for college share in a model where the outcome is in changes, not levels.

We assembled data on the date of opening of all colleges and universities in France, Germany, Great Britain, Italy, and the United States. In our baseline specification, we use the logarithm of the driving distance between each Local Labor Market in our sample and the nearest 4-year college or university among the colleges or universities that existed 20 years before the year of the relevant country's manufacturing peak. In additional specifications, we use definitions of the instrument based on proximity to institutions that existed 30, 40 or 50 years before the year of the relevant country's manufacturing peak.

In practice, the instrument is defined as *Log(1 + Distance)*, where driving distance is measured in kilometers and we add 1 to avoid dropping cities where distance is 0. Appendix Figure A.2 shows the distribution of distance. In the case of our baseline definition in the top left panel, the mean and median distances are 108.59 Km and 72.08 Km, respectively. The mean and median distances in the case of the three alternative definitions are not very different. A comparison of the lower right panel (50 years) with the upper left panel (20 years) indicates that the mean and median distance decrease only by 2.8 and 3.69 kilometers, respectively. This is a small change, indicating that the majority of the colleges and universities in our five countries were founded more than 50 years before each country's manufacturing peak. In the period between 20 and 50 years before each country's peak the number of new institutions is limited, so that the minimum distance changes only marginally. In this period, the total number of institutions grows only by 2.6%.

4.2.2 Identifying Assumption and Threats to Validity

In the baseline specification, the identifying assumption is that the 20-year lagged driving distance to college and universities is orthogonal to the term $u_{lc(l)}$ in Equation 1. The assumption requires that distance is orthogonal to employment shocks taking place between the year of manufacturing peak and 2010 caused by a shift in the unobserved determinants of local labor demand or supply. For example, for the UK and US—where the manufacturing peak takes place in 1970—our assumption is that the driving distance to the nearest college or university founded before 1950 is uncorrelated with changes to unobserved shifters of labor demand or supply that occur between 1970 and 2010, conditional on the 1970 share of college graduates and the 1970 share of employment in manufacturing.[18] The assumption is weaker if we define the instrument based on proximity measured 50 years before the manufacturing peak. In this case, our assumption for the US and the UK requires that colleges and universities founded before 1920 are not systematically placed

[18]For France and Italy, whose peak is in 1980, the instrument is defined based on institutions founded before 1960; for Germany the peak is in 1990, so distance is defined based on institutions founded before 1970.

near cities that between 1970 and 2010 experience shocks to the unobserved determinants of labor demand or supply.

Since in Equation 1 the dependent variable $\Delta \ln(Y_{lc})$ is in changes over time, permanent differences across cities in local factors that affect employment growth are differenced-out. Historical colleges and universities may be disproportionately located in areas with attractive consumption amenities—-cultural institutions, good schools, good restaurants, for instance—or areas with more productive characteristics—better transportation infrastructure, for example. If these local characteristics affect the level of employment but not its growth in the years after the manufacturing peak, the exclusion restriction is not violated.

The exclusion restriction is violated if historical colleges and universities in our five countries are located in areas with unobserved characteristics that are improving, or are constant but are increasingly attractive to workers or firms. This would be the case, for instance, if historical colleges and universities tend to be located near cities that offer better permanent amenities and the attractiveness of such amenities increases over time. In this case, labor supply–and therefore employment–would increase more in cities close to historical colleges and universities, but this increase would simply reflect the increasing attraction of the amenities rather than the causal effect of a college-educated population. Different is the case of endogenous changes in local amenities, which are not necessarily a violation of the exclusion restriction. Proximity to a college may result in more college graduates living in the area and, as a consequence, in endogenous improvements of local amenities which in turn attract even more college graduates (Diamond, 2016). This represents a possible channel through which the initial presence of a college or university raises the share of college graduates in a Local Labor Market–ultimately local employment–not a threat to the validity of the instrument.[19]

The exclusion restriction is also violated if the opening of colleges and universities in a Local Labor Market reflects changes in the demand for higher education, as opposed to its supply. In the UK and US, for example, our assumption would be invalid if colleges and universities founded before 1950 are more likely to be placed near cities that are expected to experience large employment gains between 1970 and 2010. In this case, college proximity in 1950 might be the effect of expected employment growth between 1970 and 2010, not its cause. More in general, if new colleges and universities tend to locate in cities where demand for higher education is rising, and demand for education is correlated with omitted factors that increase employment growth, then our identifying assumption would be violated.

To shed some light on the relevance of these concerns, Figure 9 shows the evolution

[19]The same conclusion applies to the case of endogenous productive amenities, whereby proximity to a college or university results in more college graduates living in the area and an endogenous improvement in local productivity, as in the case of models with human capital externalities.

of total employment before and after each country's manufacturing peak, by quartile of distance to the nearest historical college or university. The Figure shows that Local Labor Markets that are closer to a historical college or university do not appear to have steeper pre-trends in the decades leading up to the relevant manufacturing peak. If anything, Local Labor Markets in the top quartile–meaning those with the longest distance–experience a slightly steeper employment growth between $t-2$ and $t-1$. By contrast, in the decades after the relevant manufacturing peak, Local Labor Markets in the bottom quartile—i.e. those that are closest to a historical college or university—grow the fastest in terms of employment, while Local Labor Markets in the top quartile have a lower rate of growth.

Figure 10 shows a similar pattern for employment in Human Capital and Knowledge Intensive Services. Local Labor Markets that are close to a historical college or university and those that are far have similar pre-trends in the decade before the manufacturing peak. It is only in the decades after the relevant manufacturing peak that employment in Local Labor Markets in the bottom quartile grows faster than employment in Local Labor Markets in the top quartile.

In levels, Local Labor Markets that are close to historical colleges may very well be different from Local Labor Markets that are further away. But there is not much evidence that in the decades before the relevant country's manufacturing peak, total employment in Local Labor Markets that are close to historical colleges is growing any faster than employment in Local Labor Markets that are further away. This is also true for employment in Human Capital and Knowledge Intensive Services, a sector that is arguably more at risk of violating our identifying assumption.

We note that most of the colleges and universities in our sample are historical and were created well before any shocks to labor market conditions after the peak took place. For example, it is safe to assume that the founding of Oxford University in 1345 is not directly caused by labor market shocks taking place in the Oxford Local Labor Market between 1970 and 2010. In our empirical analysis below, we probe the sensitivity of our estimates to defining the instrument based on proximity measured 30, 40 or 50 years before the manufacturing peak.

While we can't completely rule out the possibilities of reverse causality or omitted variables, the robustness of our empirical estimates to the year used to define college proximity and the evidence in Figures 9 and 10 seem consistent with the exclusion restriction.

4.3 Effect on Total Employment

Table 6 presents the OLS and 2SLS estimates of Equation 1. The entry in the first row of column 1 indicates that conditioning on country effects and initial manufacturing share, the OLS coefficient on college share is 1.02 (0.13). The negative coefficient on manu-

facturing share confirms that LLMs with initially more manufacturing employment experienced slower employment growth, consistent with the evidence in Section 3 above. In column 2 we add a control for the initial size of the LLM. In column 3 we control for whether the Local Labor Market is predominately urban, using data on urban share from Henderson and Wang (2007).

In column 4 we control for the share of high-tech manufacturing employment in the year of manufacturing peak. We seek to account for at least some of the pre-existing differences in the sectoral mix within manufacturing. It is possible that cities with a high share of college graduates in the year of manufacturing peak had a more advanced mix of manufacturing industries than cities with the same overall manufacturing share but a low share of college graduates. The share of high-tech employment is missing for French LLMs, so sample size drops from 1826 to 1478. The estimate of the coefficient on college share in column 4 is slightly larger than the one in column 1, suggesting that heterogeneity in the sectoral mix within manufacturing does not seem to affect the baseline estimates in important ways.

Columns 5 to 8 present the corresponding 2SLS estimates. The first stage coefficients, reported near the bottom of the table, indicate that cities that are more distant from a college or university have a lower share of residents with a college degree. The magnitude of the first stage coefficient is of interest in its own right. The coefficient on log distance is between -0.0028 (0.0008) and -0.0048 (0.0007), depending on the specification. It implies that a driving distance of 100 Km is associated with a 1.4 to 2.2 percentage points decline in local college share. Weak instrument tests are reported near the bottom of the table. The F-statistics range from 15.09 to 47.67.

The 2SLS estimates in the first row point to a positive effect of college share on subsequent employment growth, with coefficients ranging from 1.27 (0.57) to 2.95 (0.88). The table also reports the p-values for the test of equality between the OLS and IV coefficients. Entries indicate that the coefficients in columns 5, 6, 7, 8 are not statistically different from the corresponding OLS coefficients at conventional level (the coefficient in column 8 is statistically different at 10 percent level).

The estimate in column 8 suggests that a 1 percentage point increase in the share of local workers with a college degree in the year of the country's manufacturing peak is associated with a 2.95 larger percent change in employment per decade in the decades after the manufacturing peak. To interpret the magnitude of this effect, consider that it implies that a one standard deviation increase in college share results in a rate of employment growth per decade that is 9.1 percentage points higher, holding constant the initial share of manufacturing employment. The estimate also implies that a city at the 75th percentile of its country's college share distribution experiences a 9.6 percent faster employment growth per decade compared to an otherwise similar city at the 25th percentile.

Table 7 probes the robustness of our IV estimates to alternative definitions of the

instrument. Column 1 replicates the baseline estimates from column 8 in Table 6. In column 2, the instrument is defined as the distance to the nearest college or university 30 years before the manufacturing peak. In columns 3 and 4, we use 40 and 50 years, respectively. By comparing the baseline IV estimates with IV estimates based on colleges and universities that existed further back in time, we seek to probe the role of reverse causality and unobserved heterogeneity. Finding that our estimates vary significantly as a function of when the instrument is measured may indicate that unobserved labor demand factors or unobserved heterogeneity in amenities play a significant role.

The first stage coefficients in columns 2 to 4 at the bottom of the table are stable and similar to the one in column 1. The second stage estimates are slightly lower than the baseline one. They range from 2.63 (0.88) to 2.54 (0.83). We test whether the coefficients on College Share in columns 2 to 4 are equal to the one in column 1. None of them is statistically different. The p-values, reported in the table below the second stage coefficients, are 0.2880, 0.3260 and 0.2516, respectively. The finding that estimates of both the first and second stage are not sensitive to defining distance further back in time should not come as a complete surprise. It reflects the fact that the vast majority of the colleges and universities in our sample that exist 20 year before the relevant country manufacturing peak also exist 50 years before the peak, as discussed above. Importantly, the location of the few that are founded between 50 years before the peak and 20 years before the peak does not appear to be systematically correlated with employment changes in the decades after each country's manufacturing peak.

Based on Table 7, we conclude that estimates are robust to the definition of the instrument and that reverse causality doesn't appear very likely to bias our baseline estimates. We have also estimated models that condition on pre-trends in employment and found similar estimates. Specifically, a model like the one in columns 4 and 8 that include among the controls the change in employment between $t-1$ and 0 yields estimates equal to 1.07 (0.22) and 2.75 (0.85), respectively.

The estimates in Table 6 are based on a model that assumes that the effect of college share is the same for all cities. In Appendix Table A.1, we present estimates of a model similar to the one in Equation 1 that includes the interaction between college share and an identifier for former manufacturing hubs. This specification allows the effect of college share to vary based on whether the city is a former manufacturing hub or not. Estimates in the top panel of the Table suggest that the effect of college share for former manufacturing hubs is 0.48 percent smaller than that of other cities, although it remains positive and statistically different from zero. The sum of the two coefficients suggests that a 1 percentage point increase in the share of local workers with a college degree in the year of the country's manufacturing peak is associated with an increase in the mean decadal growth of employment in former manufacturing hubs by 2.42 percent. A test fails to reject the hypothesis that this sum is statistically different from zero (p-value: 0.002).

4.4 Effect on Employment by Sector

Having uncovered a positive effect of local college share on total employment growth during the years of manufacturing decline, we turn to employment growth in manufacturing and in Human Capital and Knowledge Intensive Services.

One possible explanation for the effect of local college share on total employment growth is that a higher college share in a Local Labor Market is associated with a more limited decline of manufacturing employment. This could happen, for example, if employment in advanced or high tech manufacturing is initially over-represented in Local Labor Markets with a high initial college share and it declines less than overall manufacturing employment.

However, the empirical evidence does not appear to support this hypothesis. The top panel of Figure 11 points to a *negative* correlation between initial college share and subsequent employment growth in manufacturing (both in deviation from country-level means), controlling for the initial share of manufacturing.

Table 8 shows the corresponding OLS and 2SLS estimates. The models are the same as the ones in Table 6. The OLS estimates are negative, while the 2SLS estimates are either negative (column 5 and 6) or statistically insignificant (columns 7 and 8). We conclude that the effect of college share on total employment growth cannot be explained by smaller job losses in manufacturing. Column 2 in Panel B of Appendix Table A.1 indicates that a similar conclusion applies to the subset of cities that are former manufacturing hubs.

By contrast, the bottom panel of Figure 11 shows a positive correlation between initial college share and subsequent employment growth in Human Capital and Knowledge Intensive Services in the UK and US (both in deviation from country-level means), controlling for the initial share of manufacturing. The slope is 0.91 (0.36), indicating that cities with an initially high college share experienced faster employment growth in human capital intensive services in the decades after their country's manufacturing peak compared to cities in the same country with an initially low college share. Table 9 reports the corresponding OLS and 2SLS estimates. The estimates in columns 4 and 8 indicate that a 1 percentage point increase in the share of local workers with a college degree in the year of the country manufacturing peak is associated with an increase in the mean decadal growth of employment in Human Capital and Knowledge Intensive Services by 1.30 (0.33) and 4.33 (2.58) percent in the decades after the manufacturing peak, respectively.[20] The estimate in column 8 indicates that an increase in the college share by one standard deviation results in an employment growth per decade that is 17.2 percent larger, holding constant the initial share of manufacturing employment. We stress, however, that the estimate in column 8 is imprecise and statistically significant only at the 10% level.

[20]This finding is consistent with findings by Quintana (2021).

In Panel C in Appendix Table A.1, we allow the effect to vary based on whether the city is a former manufacturing hub or not. Estimates suggest that the effect of college share is 0.78 percent smaller for former manufacturing hubs.

Finally, in the bottom panel we report estimates for growth in employment in services that are not Human Capital and Knowledge Intensive.[21] By definition, these industries should be less sensitive to the initial level of human capital in the Local Labor Market. The point estimates in column 4 and 8 indicate that an increase in college share does not raise employment in this sector, although the precision of the estimates is low and it precludes to draw definitive conclusions.

5 Conclusions

The decline of manufacturing employment is one of the most important and consequential changes that have taken place in the labor market of industrialized countries over the past 50 years. In this paper, we study the experience of 1,993 cities to provide a comprehensive analysis of empirical regularities across six industrialized economies.

We uncover a significant amount of heterogeneity in the employment effect of deindustrialization. In the majority of former manufacturing hubs, total employment declined when manufacturing employment declined. However, a large fraction of cities were able to adapt to the negative shock caused by deindustrialization and successfully reinvent their local economy. In 34% of cases total employment increased (relative to the country mean). We consider this a surprisingly high number.

We find that one important factor that raised the probability of recovery was the share of workers with a college degree in the local labor force in the year of the country manufacturing peak. Cities that had a higher share of college graduates in the labor force in the year of their country's manufacturing peak experienced faster total employment growth in the years after the manufacturing peak compared to cities in the same country that had the same initial share of local manufacturing employment but a lower share of college graduates.

The timing of this effect is revealing. In the period before the onset of deindustrialization, the local share of college graduates was not an important driver of local employment growth. By contrast, during the period of deindustrialization, the local share of college graduates has become an increasingly important predictor of local employment growth, possibly reflecting a shift in employment among industrialized countries toward human capital-intensive industries

Consistent with this possibility, we find that a channel through which local human capital affected employment growth was job creation in human capital-intensive services.

[21] This sector is defined so that the sum of employment Human Capital and Knowledge Intensive Services and the non Human Capital and Knowledge Intensive Services is equal to total employment in Services.

In cities with an initially high share of college graduates, the loss of manufacturing employment was offset by gains in service industries, and in particular in Human Capital and Knowledge Intensive Services.

6 Bibliography

Abraham, K. G. and M. S. Kearney (2020). Explaining the decline in the us employment-to-population ratio: A review of the evidence. *Journal of Economic Literature 58*(3), 585–643.

Acemoglu, D., D. Autor, D. Dorn, G. H. Hanson, and B. Price (2016). Import competition and the great us employment sag of the 2000s. *Journal of Labor Economics 34*(S1), S141–S198.

Acemoglu, D., D. Dorn, G. H. Hanson, B. Price, et al. (2014). Return of the solow paradox? it, productivity, and employment in us manufacturing. *American Economic Review 104*(5), 394–99.

Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy 128*(6), 2188–2244.

Andes, S., M. Horowitz, R. Helwig, and B. Katz (2017). Capturing the next economy: Pittsburgh's rise as a global innovation city. *Brookings Institution — The Bass Initiative on Innovation and Placemaking*.

Andrews, M. (2023). How do institutions of higher education affect local invention? evidence from the establishment of u.s. colleges. *American Economic Journal: Economic Policy*.

Andrews, M., L. Russell, and L. Yu (2023). Higher education and local educational attainment: Evidence from the establishment of u.s. colleges. *Review of Economics and Statistics*.

Armstrong, B. (2021). Industrial policy and local economic transformation: Evidence from the u.s. rust belt. *Economic Development Quarterly, Vol. 35(3) 181–196*.

Autor, D., D. Dorn, and G. Hanson (2019). When work disappears: Manufacturing decline and the falling marriage-market value of men. *American Economic Review: Insights 1(2)*.

Autor, D., D. Dorn, and G. H. Hanson (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review 103*(6), 2121–68.

Baily, M. N. and B. P. Bosworth (2014). Us manufacturing: Understanding its past and its potential future. *Journal of Economic Perspectives 28*(1), 3–26.

Banasick, S. and R. Hanham (2008). Regional decline of manufacturing employment in japan during an era of prolonged stagnation. *Regional Studies 42*(4), 489–503.

Bartik, T. J. (2018). Helping manufacturing-intensive communities: What works? Technical report, Center on Budget and Policy Priorities.

Benedetto, J. (2018). Trends in Manufacturing Employment in the Largest Industrialized Economies during 1998-2014. Technical report, USITC Executive Briefings on Trade, April. Washington, DC: U.S. International Trade Commission.

Brandily, P., M. Distefano, H. Donnat, I. Feld, H. G. Overman, and K. Shah (2022). Bridging the gap: What would it take to narrow the uk's productivity disparities? *The Resolution Foundation*.

Card, D. (1993). Using geographic variation in college proximity to estimate the return to schooling. *NBER working paper* (w4483).

Card, D. (2001). Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica 106*(3), 479–524.

Carneiro, P. M., K. Liu, and K. G. Salvanes (2018). The supply of skill and endogenous technical change: evidence from a college expansion reform. *NHH Dept. of Economics Discussion Paper* (16).

Charles, K. K., E. Hurst, and M. J. Notowidigdo (2016). The masking of the decline in manufacturing employment by the housing bubble. *Journal of Economic Perspectives 30*(2), 179–200.

Charles, K. K., E. Hurst, and M. J. Notowidigdo (2019). Housing booms, manufacturing decline and labour market outcomes. *The Economic Journal 129*(617), 209–248.

Charles, K. K., E. Hurst, and M. Schwartz (2019). The transformation of manufacturing and the decline in us employment. *NBER Macroeconomics Annual 33*(1), 307–372.

Ciani, E., F. David, and G. de Blasio (2017). Local labour market heterogeneity in Italy: estimates and simulations using responses to labour demand shocks. Temi di discussione (Economic working papers) 1112, Bank of Italy, Economic Research and International Relations Area.

Coombes, M. G., A. E. Green, and S. Openshaw (1986). An Efficient Algorithm to Generate Official Statistical Reporting Areas: The Case of the 1984 Travel-to-Work Areas Revision in Britain. *The Journal of the Operational Research Society 37*(10), 943–953.

Criscuolo, C., R. Martin, H. G. Overman, and J. Van Reenen (2018). Some causal effects of an industrial policy. *American Economic Review*.

Currie, J. and E. Moretti (2003). Mother's education and the intergenerational transmission of human capital: Evidence from college openings. *The Quarterly journal of economics 118*(4), 1495–1532.

Daniele, V., P. Malanima, and N. Ostuni (2018). Geography, market potential and industrialization in italy 1871–2001. *Papers in Regional Science 97*(3), 639–662.

Dauth, W., S. Findeisen, and J. Suedekum (2014). The rise of the east and the far east: German labor markets and trade integration. *Journal of the European Economic Association 12*(6), 1643–1675.

Dauth, W., S. Findeisen, and J. Suedekum (2021). Adjusting to globalization in germany. *Journal of Labor Economics 39*(1), 263–302.

Department of Employment (1984). *Revised Travel-to-Work Areas*. Occasional Supplement No. 3 Issued With Employment Gazette Vol. 92, No. 9, September 1984.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980-2000. *American Economic Review 106*(3), 479–524.

Duranton, G. (2007). Urban evolutions: The fast, the slow, and the still. *American Economic Review 97*(1), 197–221.

Duranton, G. and H. G. Overman (2008). Exploring the detailed location patterns of uk manufacturing industries using microgeographic data. *Journal of Regional Science*.

Dustmann, C., B. Fitzenberger, U. Schönberg, and A. Spitz-Oener (2018). From sick man of europe to economic superstar: Germany's resurgence and the lessons for europe. *Explaining Germany's Exceptional Recovery*, 21.

Ehrlich, M. V. and H. G. Overman (2020). Place-based policies and spatial disparities across european cities. *Journal of Economic Perspectives 34*(3), 128–49.

Eurostat (2020a). Aggregations of manufacturing based on nace rev 1.1. https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an2.pdf. Accessed at 18/03/2021.

Eurostat (2020b). High-tech industry and knowledge-intensive services (htec). https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm. Accessed at 18/03/2021.

Feng, S. and X. Xia (2021). Heterogeneous firm responses to increases in high-skilled workers: Evidence from China's college enrollment expansion. Mimeo, University of Essex.

Findeisen, S. and J. Südekum (2008). Industry churning and the evolution of cities: Evidence for germany. *Journal of Urban Economics 64*(2), 326–339.

Fort, T. C., J. R. Pierce, and P. K. Schott (2018). New perspectives on the decline of us manufacturing employment. *Journal of Economic Perspectives 32*(2), 47–72.

Garin, A. (2019). Public investment and the spread of "good-paying" manufacturing jobs: Evidence from world war ii's big plant. *Working Paper*.

Gathmann, C., I. Helm, and U. Schönberg (2020). Spillover effects of mass layoffs. *Journal of the European Economic Association 18*(1), 427–468.

Gennaioli, N., R. La Porta, F. L. De Silanes, and A. Shleifer (2014). Growth in regions. *Journal of Economic growth 19*(3), 259–309.

Glaeser, E. L. (2005). Reinventing boston: 1630–2003. *Journal of Economic Geography 5*(2), 119–153.

Glaeser, E. L. (2009). The death and life of cities. In *Making cities work: Prospects and policies for urban America*, pp. 22–62. Princeton University Press.

Glaeser, E. L. and A. Saiz (2004). The rise of the skilled city. *Brookings-Wharton Papers on Urban Affairs*, 47–105.

Goldin, C. and L. Katz (1999). The shaping of higher education: The formative years in the united states. *Journal of Economic Perspectives V*, 37–62.

Gruber, J. and S. Johnson (2019). *Jump-starting America: How breakthrough science can revive economic growth and the American dream*. Hachette UK.

Hanson, G. and R. Livas (2023). Did the rise of the south deindustrialize the north? *Mimeo, Harvard University*.

Henderson, J. V. and H. G. Wang (2007). Urbanization and city growth: The role of institutions. *Regional Science and Urban Economics 37*(3), 283–313.

Hornbeck, R. and E. Moretti (2021). Estimating who benefits from productivity growth: Local and distant effects of city productivity growth on wages, rents, and inequality.

Houseman, S. N. (2018). Understanding the decline of us manufacturing employment.

Howard, G. and R. Weinstein (2022). Workhorses of opportunity: Regional universities increase local social mobility. *Working Paper*.

Howard, G., R. Weinstein, and Y. Yang (2021). Do universities improve local economic resilience? *IZA Discussion Paper No. 14422*.

IMF (2018). *Chapter 3. Manufacturing Jobs: Implications for Productivity and Inequality*, pp. ch003. USA: International Monetary Fund.

Inman, R. (2009). *Making cities work: Prospects and policies for urban America*. Princeton University Press.

Kahn, M. E. and M. McComas (2021). *Unlocking the Potential of Post-Industrial Cities*. Johns Hopkins University Press.

Kanemoto, Y. and K. Tokuoka (2002). Proposal for the standards of metropolitan areas of japan. *Journal of Applied Regional Science 7*, 1–15.

Kantor, S. and A. Whalley (2014). Knowledge spillovers from research universities: Evidence from endowment value shocks. *Review of Economics and Statistics 96*.

Kantor, S. and A. Whalley (2019). Research proximity and productivity: Long-term evidence from agriculture. *Journal of Political Economy 127*.

Kantor, S. and A. Whalley (2022). Moonshot: Public rd and growth. *Working Paper*.

Kosfeld, R. and A. Werner (2012). Deutsche arbeitsmarktregionen–neuabgrenzung nach den kreisgebietsreformen 2007–2011. *Raumforschung und Raumordnung 70*(1), 49–64.

Krueger, A. B. (2017). Where have all the workers gone? an inquiry into the decline of the us labor force participation rate. *Brookings papers on economic activity 2017*(2), 1.

Marchand, O. and C. Minni (2019). The major transformations of the french labour market since the early 1960s. *Economie et Statistique 510*(1), 89–107.

Mills, K., C. Elkins, V. Gandhi, G. Elanbeck, and Z. Gillman (2022). Pittsburgh: A successful city? *Harvard Business School Case 322-080*.

Moretti, E. (2004). Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of econometrics 121*(1-2), 175–212.

Moretti, E. (2010). Local multipliers. *American Economic Review 100*(2), 373–77.

Moretti, E. and P. Thulin (2013, 01). Local multipliers and human capital in the United States and Sweden. *Industrial and Corporate Change 22*(1), 339–362.

Nimier-David, E. (2022). Local Human Capital and Firm Creation: Evidence from the Massification of Higher Education in France. Mimeo, CREST.

Overman, H. G. and D. Puga (2002). Unemployment clusters across european countries and regions. *Economic Policy*.

Peri, G. (2002). Globalization, rigidities and national specialization: a dynamic analysis. *Structural Change and Economic Dynamics*.

Pierce, J. R. and P. K. Schott (2016). The surprisingly swift decline of us manufacturing employment. *American Economic Review 106*(7), 1632–62.

Quintana, J. (2021). Import competition, regional divergence, and the rise of the skilled city.

Rice, P. and A. J. Venables (2020). The persistent consequences of adverse shocks: how the 1970s shaped uk regional inequality.

Rodes, C. (2020). Manufacturing: statistics and policy. Briefing Paper 01942, House of Commons Library.

Ronsac, J.-J. (1994). Le Nouveau Découpage en Zones d'Emploi: Un Outil Pour la Connaissance et l'Action. *Courrier des Statistiques 70*, 33–35.

Rosenthal, S. S. and S. L. Ross (2015). Change and persistence in the economic status of neighborhoods and cities. *Handbook of regional and urban economics 5*, 1047–1120.

Sforzi, F. (1997). *I Sistemi Locali del Lavoro 1991*. Rome: Istituto Nazionale di Statistica (ISTAT).

Sianesi, B. and J. Van Reenen (2003). Education and economic growth: A review of the literature. *Journal of Economic Survey*.

Turok, I. and N. Edge (1999). *The jobs gap in Britain's cities*. Policy P.

Valero, A. and J. Van Reenen (2019). The economic impact of universities: Evidence from across the globe. *Economics of Education Review 68*, 53–67.

Van Dijk, J. (2014). Local multipliers in oecd regions. Technical report, Working Paper.

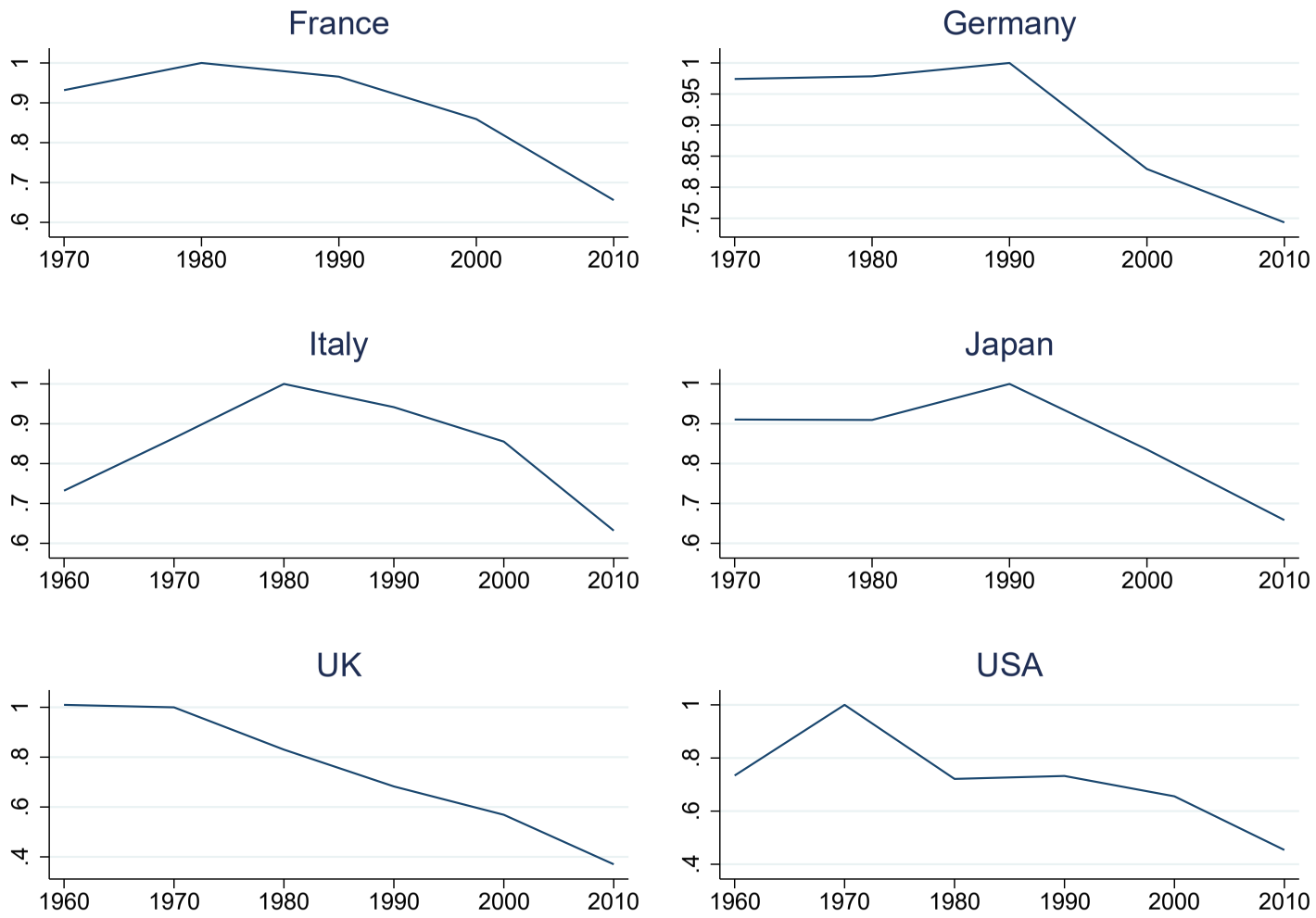
Von Wachter, T. (2010). Summary of the literature on job displacement in the us and eu: What we know and what we would like to know. *Wage structures, employment adjustments and globalization: Evidence from linked and firm-level panel data*, 64–121.

Von Wachter, T. (2020). The persistent effects of initial labor market conditions for young adults and their sources. *Journal of Economic Perspectives 34*(4), 168–94.

Weaver, A. and P. Osterman (2017). Skill demands and mismatch in us manufacturing. *ILR Review 70*(2), 275–307.

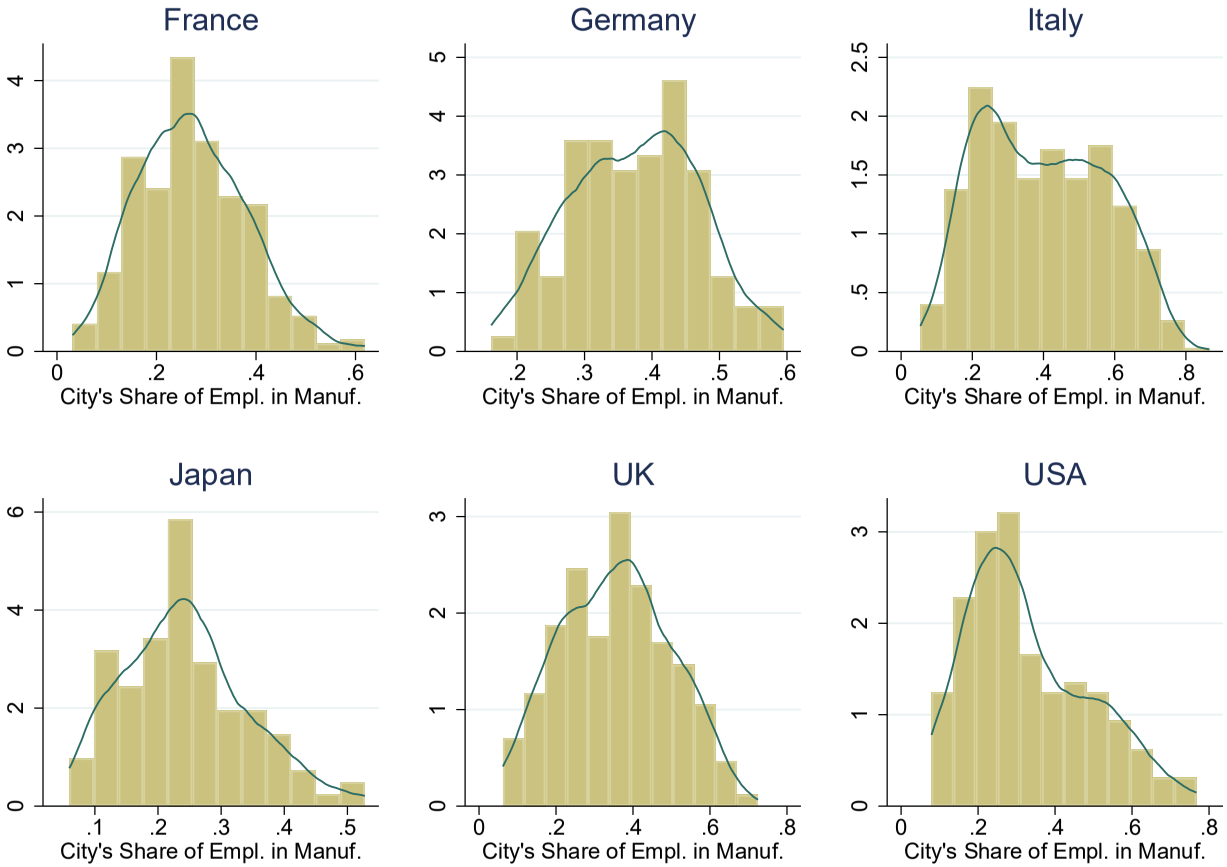
Wolman, H., H. Wial, T. S. Clair, and E. Hill (2017). *Coping with Adversity: Regional Economic Resilience and Public Policy*. Cornell University Press.

Figure 1: Employment in Manufacturing, by Country.



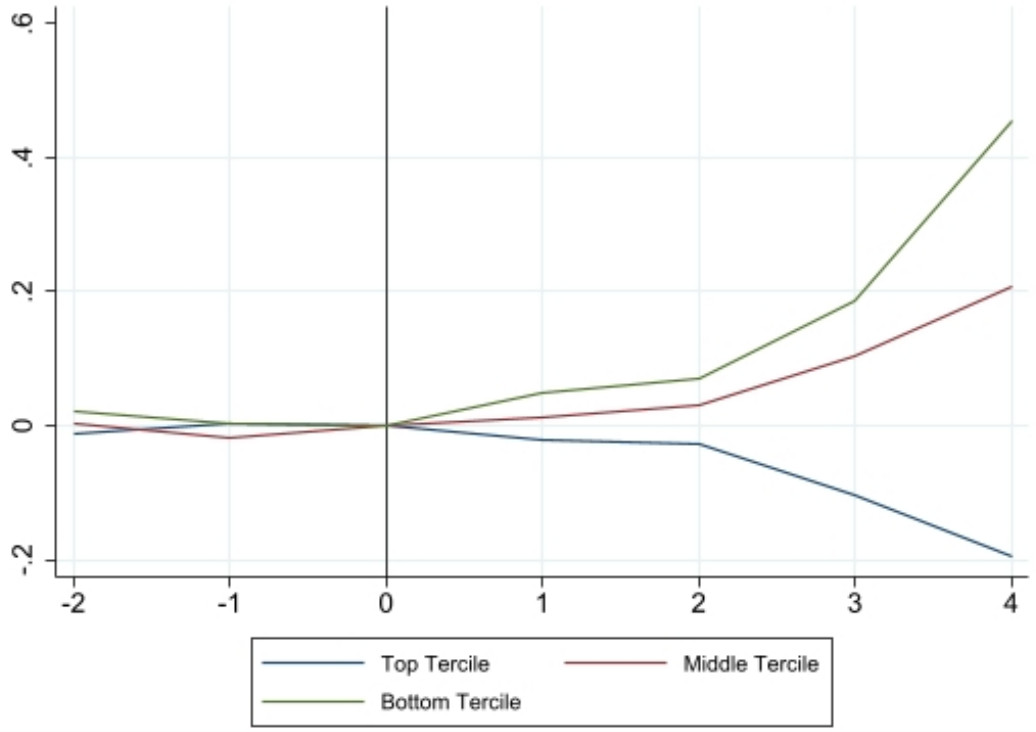
Note: Manufacturing employment in a country is normalized to 1 in the year of the country's manufacturing peak.

Figure 2: Spatial Distribution of the Share of Manufacturing Employment in the Year of Manufacturing Peak, by Country.



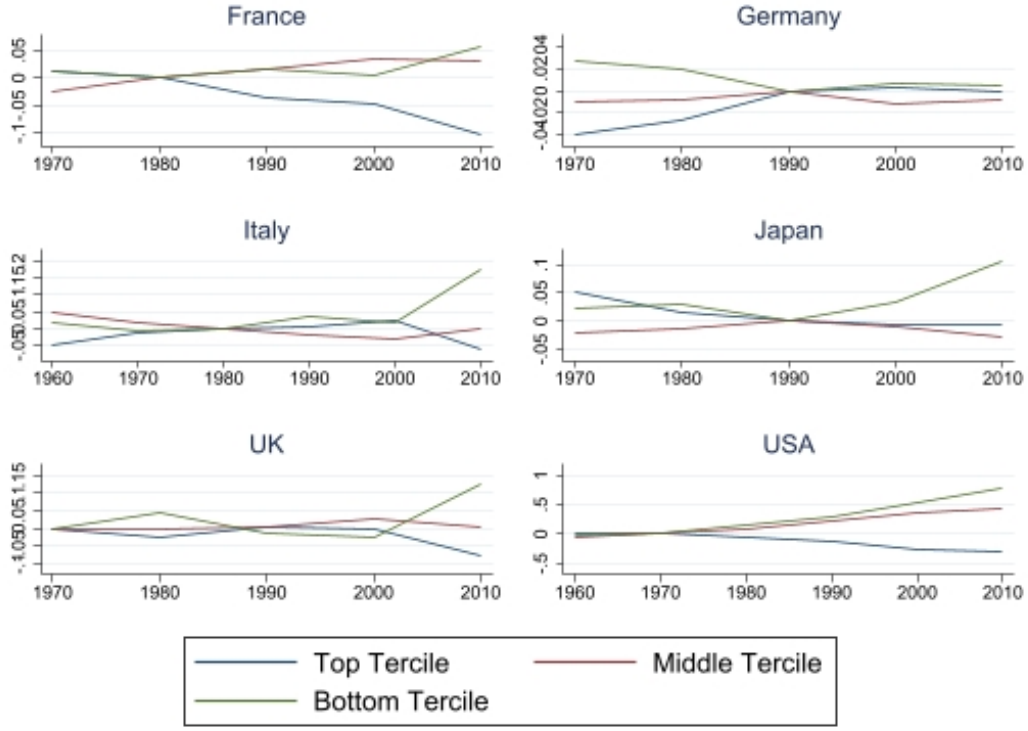
Note: The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany and Japan.

Figure 3a: Total Employment Before and After the Year of Manufacturing Peak, by Initial Manufacturing Share Tercile



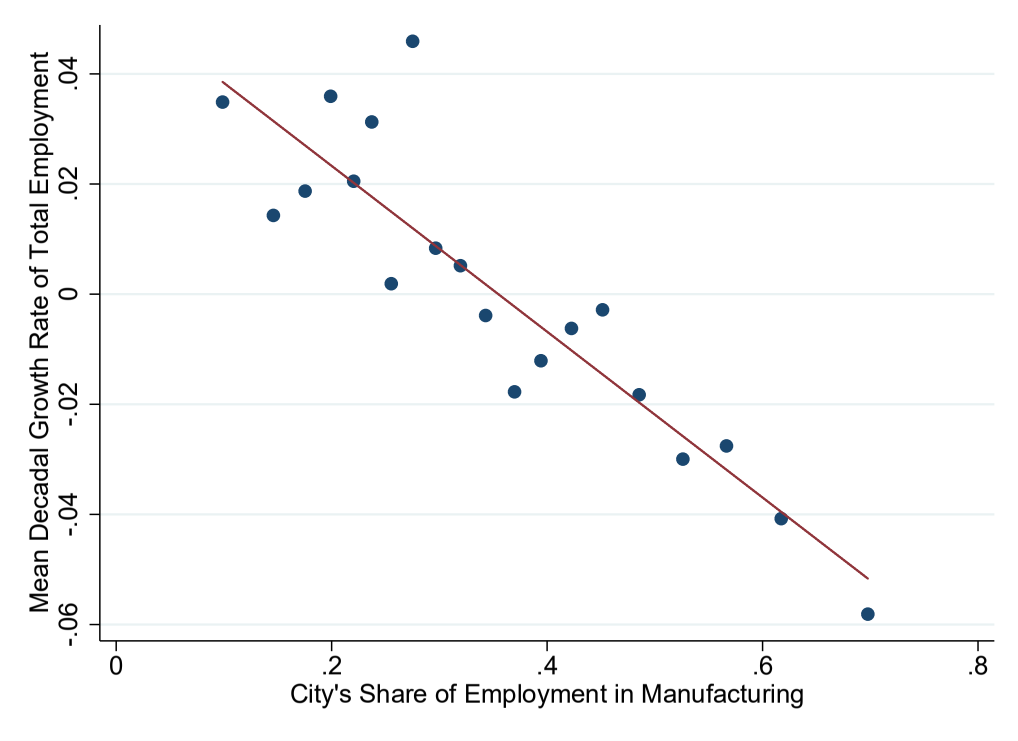
Note: Time $t = 0$ on the x-axis represents the year of the the relevant country's manufacturing peak. Local Labor Markets are divided in three groups based on the share of manufacturing employment measured in the year of the relevant country's manufacturing peak. "Top Tercile" includes Local Labor Markets that in the year of their country's manufacturing peak had a share of manufacturing employment in the top tercile of their country's distribution. The "Middle Tercile" and "Bottom Tercile" are defined similarly. The Figure shows the percent difference between total employment in a given decade and total employment at the time of the country's manufacturing peak. The change in employment for a given city is computed in deviation from its country's mean. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany and Japan. Germany includes only Local Labor Markets in West Germany.

Figure 3b: Total Employment Before and After the Year of Manufacturing Peak, by Manufacturing Share Tercile and Country



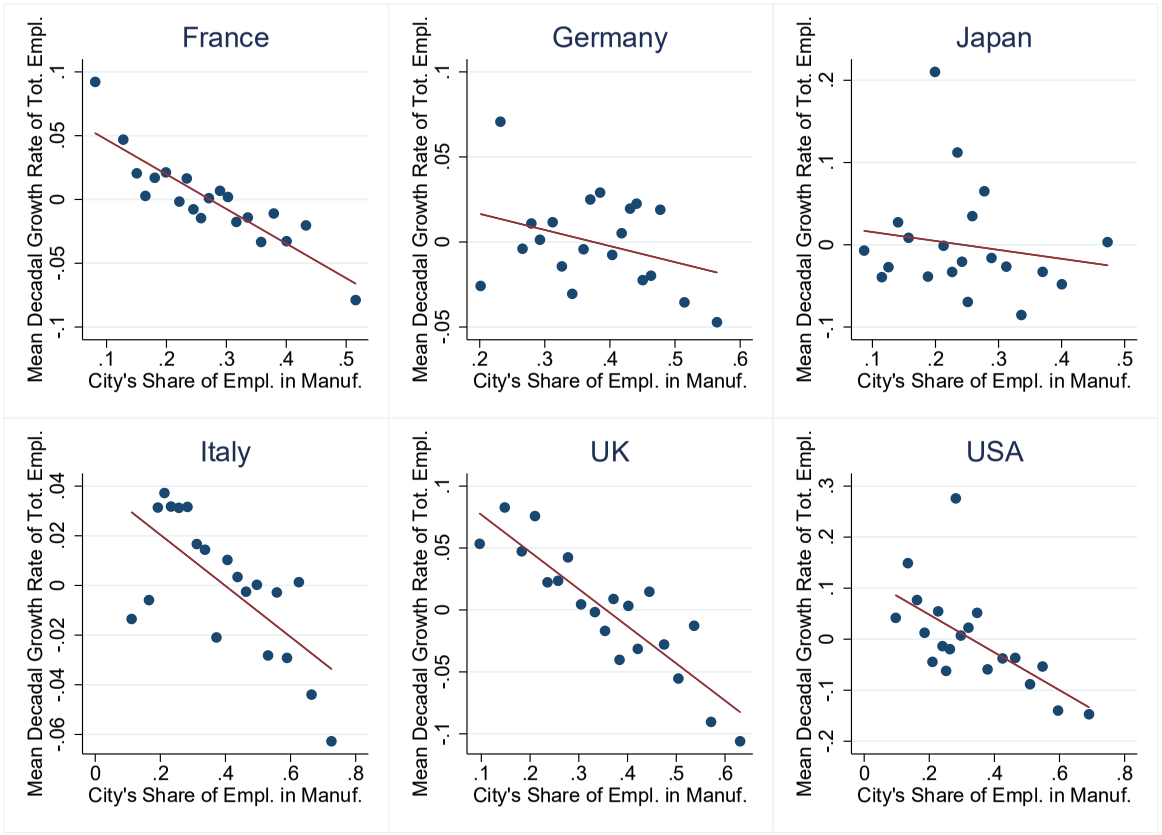
Note: Local Labor Markets are divided in three groups based on the share of manufacturing employment measured in the year of manufacturing peak. "Top Tercile" includes the Local Labor Markets that in the year of their country's manufacturing peak had a share of manufacturing employment in the top tercile of their country's distribution. The "Middle Tercile" and "Bottom Tercile" are defined similarly. The Figure shows the percent difference between total employment in a given decade and total employment at the time of the country's manufacturing peak. The change in employment for a given city is computed in deviation from its country's mean. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany and Japan. Germany includes only Local Labor Markets in West Germany.

Figure 4a: Initial Share of Employment in Manufacturing and Subsequent Mean Decadal Growth Rate of Total Employment



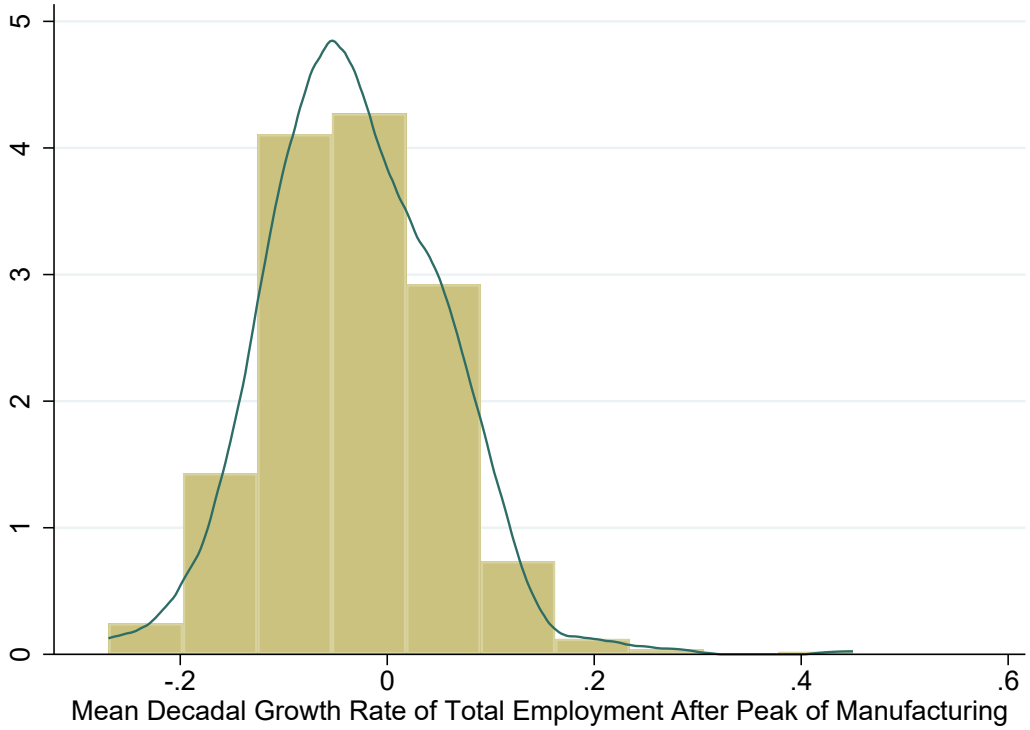
Note: Binned scatter plot. The share of employment in manufacturing on the x-axis is measured in the year of the relevant country's manufacturing peak. The mean decadal growth rate of total employment on the y-axis is computed between the year of the relevant country's manufacturing peak and 2010 and is expressed in deviation from the country-level mean decadal growth rate. The solid line shows the best linear fit estimated on the underlying Local Labor Market data. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany and Japan Germany includes only Local Labor Markets in West Germany.

Figure 4b: Initial Share of Employment in Manufacturing and Subsequent Mean Decadal Growth Rate of Total Employment, By Country



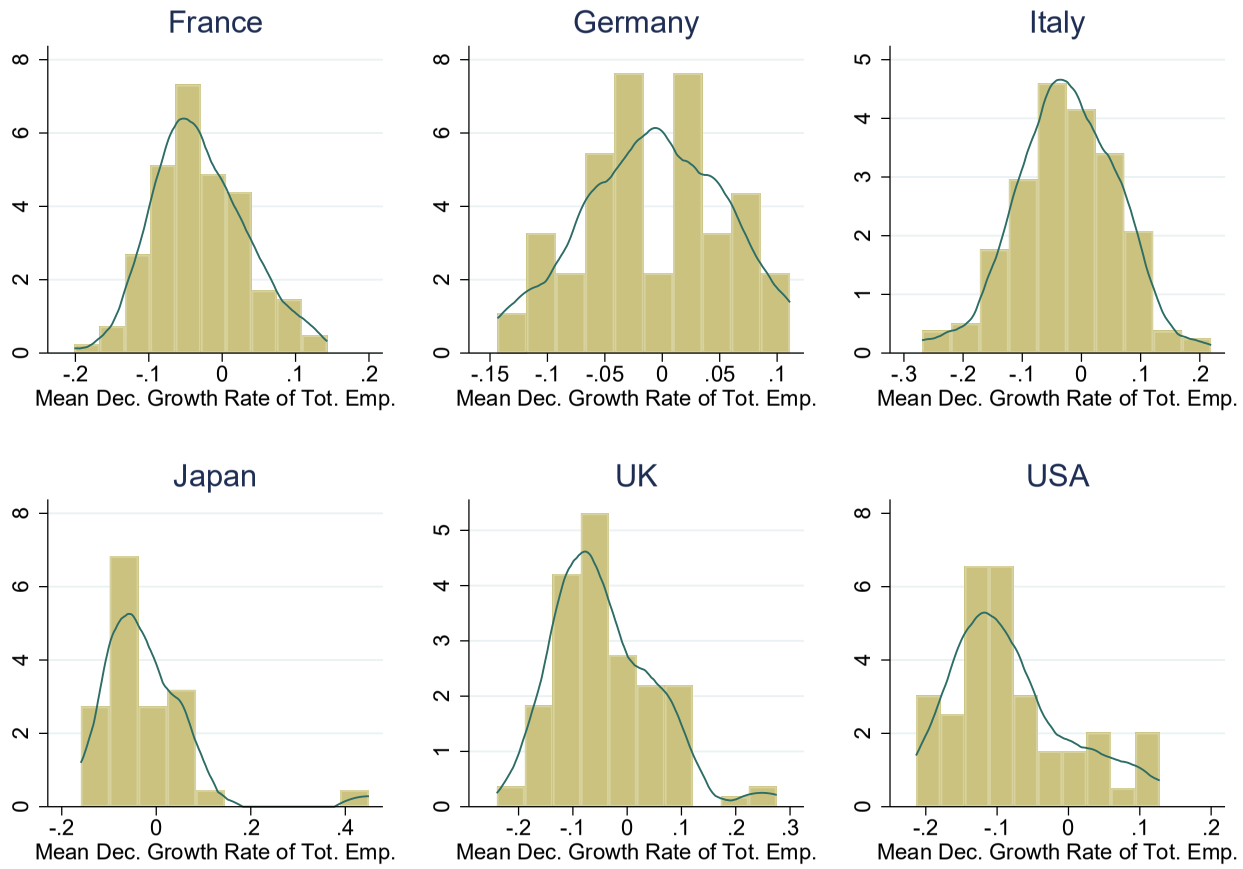
Note: Binned scatter plot. The share of employment in manufacturing on the x-axis is measured in the year of the relevant country's manufacturing peak. The mean decadal growth rate of total employment on the y-axis is computed between the year of the relevant country's manufacturing peak and 2010 and is expressed in deviation from the country-level mean decadal growth rate. The solid line shows the best linear fit estimated on the underlying Local Labor Market data. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany and Japan Germany includes only Local Labor Markets in West Germany.

Figure 5a: Spatial Distribution of Mean Decadal Growth Rate of Total Employment After Peak of Manufacturing in Former Manufacturing Hubs



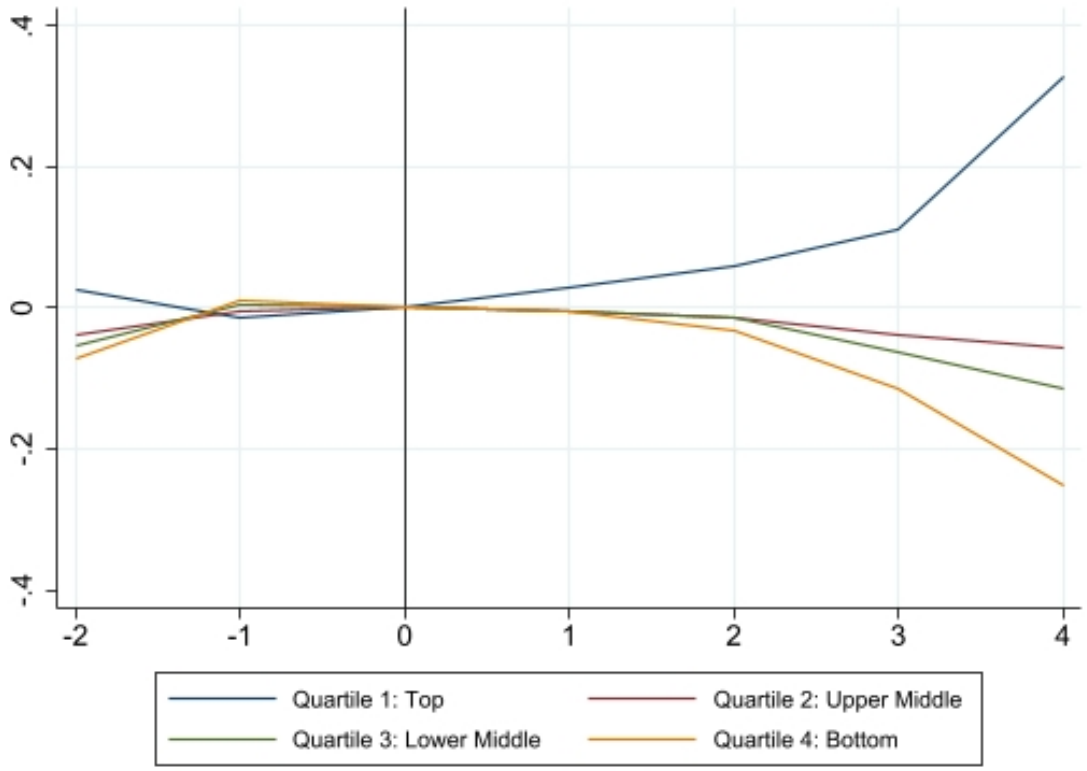
Note: The city-level mean decadal growth rate of total employment after manufacturing peak is expressed in deviation from the country-level mean decadal growth rate. The sample includes former manufacturing hubs, defined as cities that in the year of their country's manufacturing peak had a local manufacturing employment in the top tercile. Germany includes only Local Labor Markets in West Germany. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany and Japan

Figure 5b: Spatial Distribution of Mean Decadal Growth Rate of Total Employment After Peak of Manufacturing in Former Manufacturing Hub, By Country



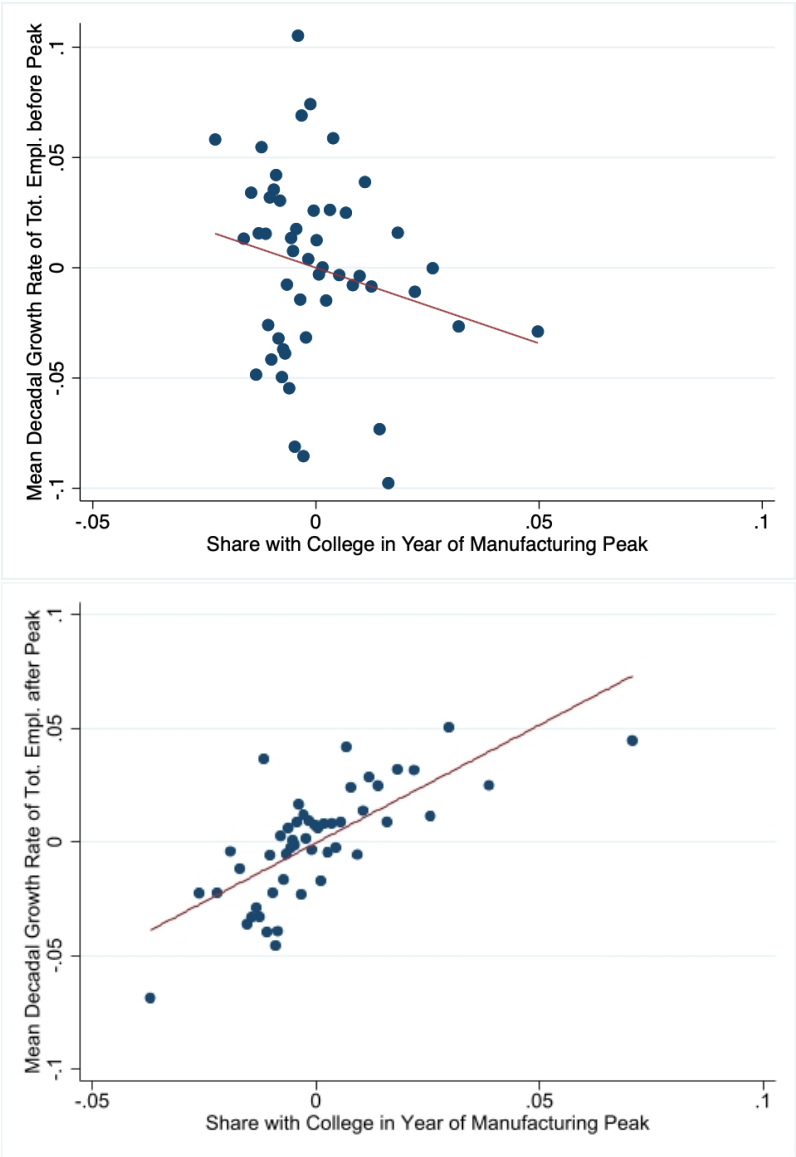
Note: The city-level mean decadal growth rate of total employment after manufacturing peak is expressed in deviation from the country-level mean decadal growth rate. The sample includes former manufacturing hubs, defined as cities that in the year of their country's manufacturing peak had a local manufacturing employment share in the top tercile. Germany includes only Local Labor Markets in West Germany. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany and Japan.

Figure 6: Total Employment Before and After the Year of Manufacturing Peak, by College Share Quartile



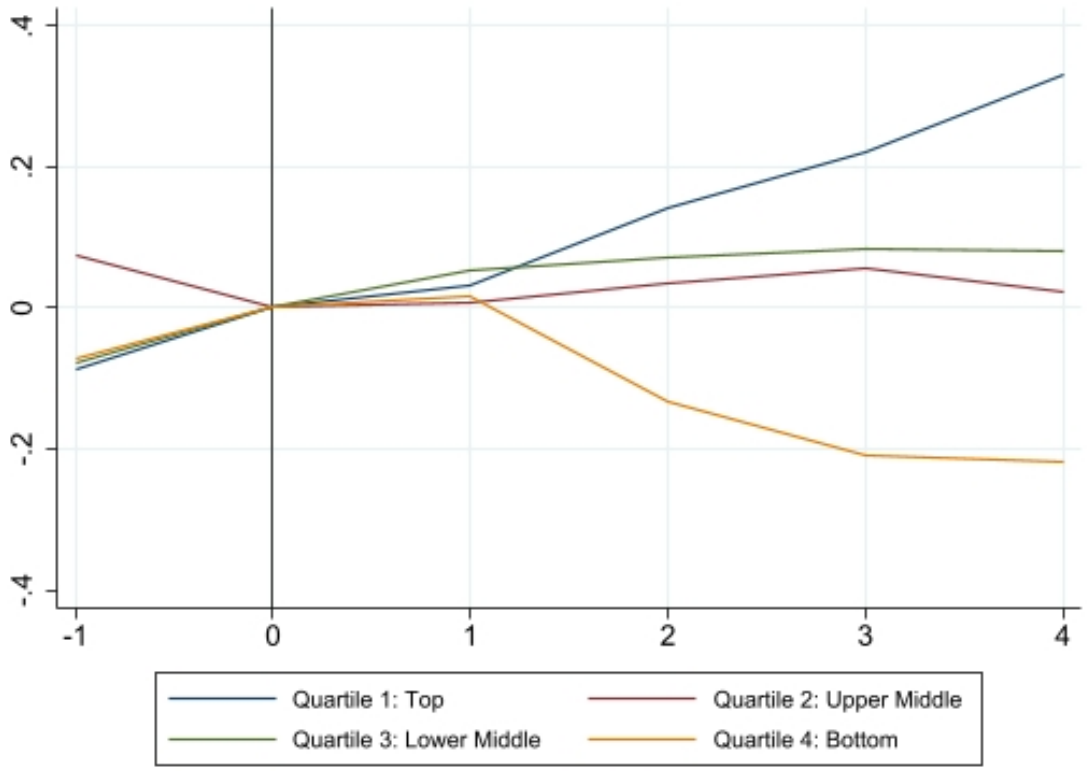
Note: "Top Quartile" includes Local Labor Markets with a share of college-educated residents in the top quartile of their country's distribution in the year of their country's manufacturing peak (t=0). The other quartiles are defined similarly. The Figure shows the percent difference between total employment in a given decade and total employment at the time of the manufacturing peak. The change in employment for a given city is computed in deviation from its country's mean. Germany includes only Local Labor Markets in West Germany. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany.

Figure 7: Change in Total Employment Before and After the Manufacturing Peak as a Function of the Share of Local Residents with a College or University Degree in Year of the Manufacturing Peak



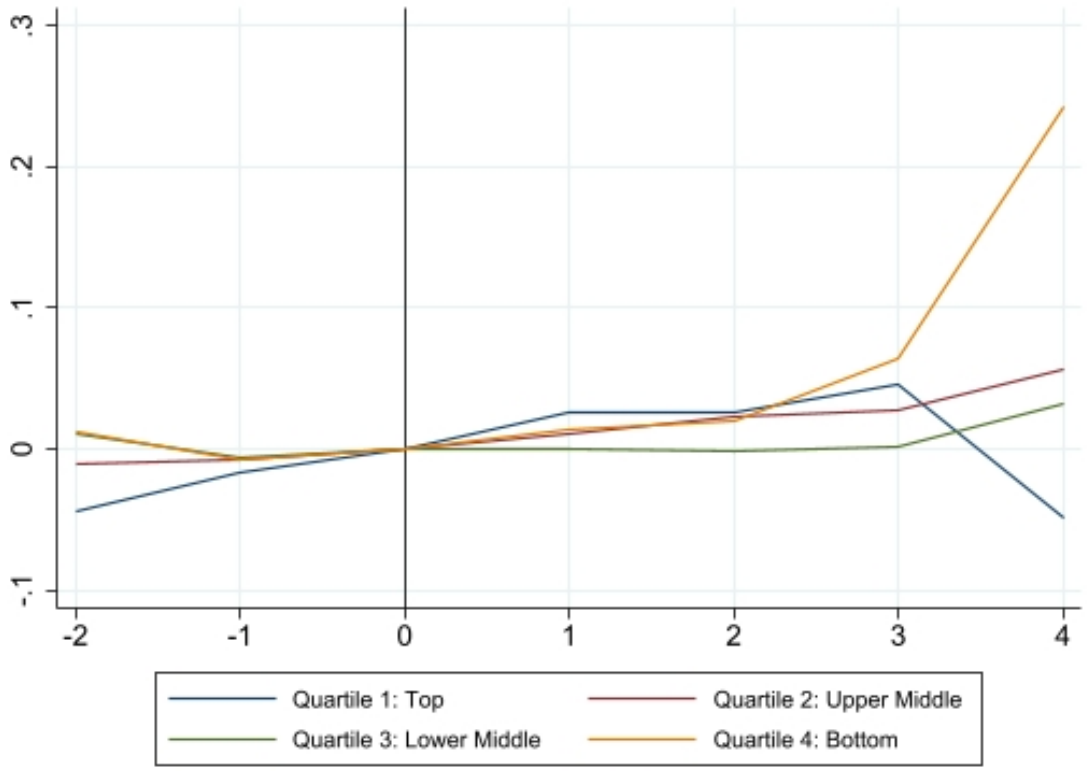
Note: Binned scatter plot. The Figure plots the initial college share on the x-axis and percent decadal employment change on the y-axis (both expressed in deviation from country-level means), controlling for the share of manufacturing at the peak. In the top panel, the percent decadal employment change is measured before the manufacturing peak (in the two decades preceding the relevant country's manufacturing peak, i.e. period between $t = -2$ and $t = 0$); in the bottom panel, employment growth is measured after the manufacturing peak (in the period between the country's manufacturing peak and 2010). The solid line shows the best linear fit estimated on the underlying Local Labor Market-level data. Germany includes only Local Labor Markets in West Germany. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany.

Figure 8: Employment in Human Capital and Knowledge Intensive Service Before and After the Year of Manufacturing Peak, by College Share Quartile



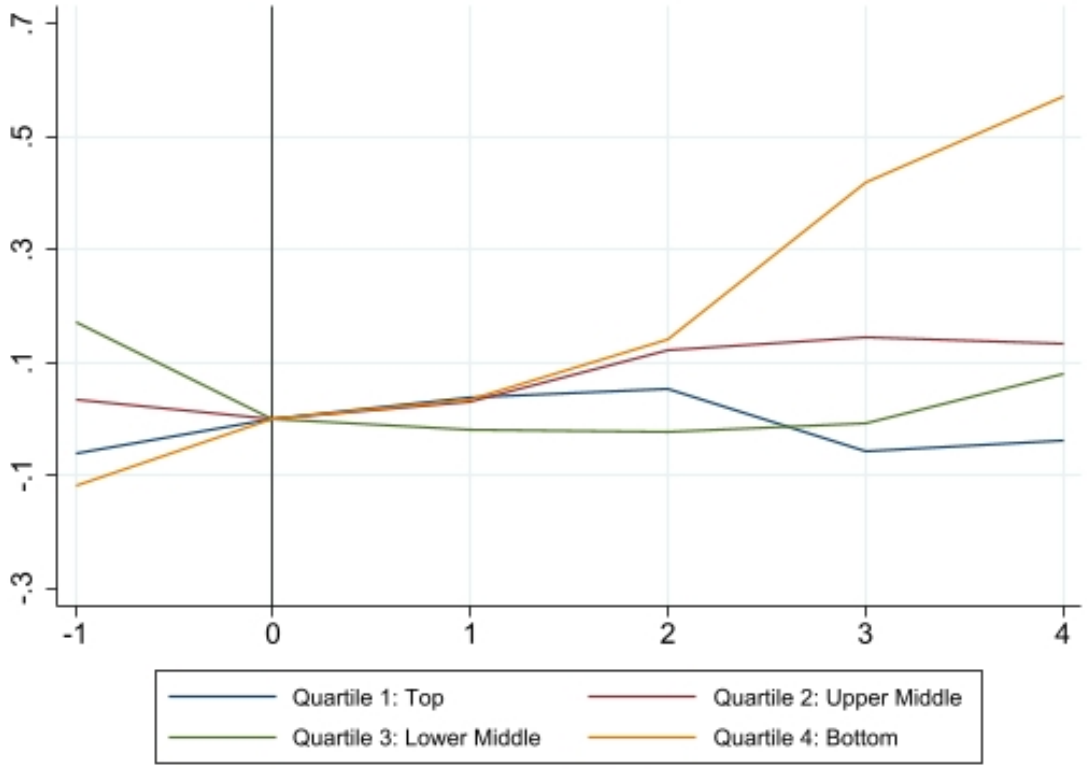
Note: "Top Quartile" includes Local Labor Markets with a share of college-educated residents in the top quartile of their country's distribution in the year of their country's manufacturing peak (t=0). The other quartiles are defined similarly. The Figure shows the percent difference between employment in a given decade and employment at the time of the manufacturing peak. The change in employment for a given city is computed in deviation from its country's mean. Data include only United Kingdom and United States.

Figure 9: Total Employment Before and After the Year of Manufacturing Peak, by Quartile of Distance from Historical Colleges



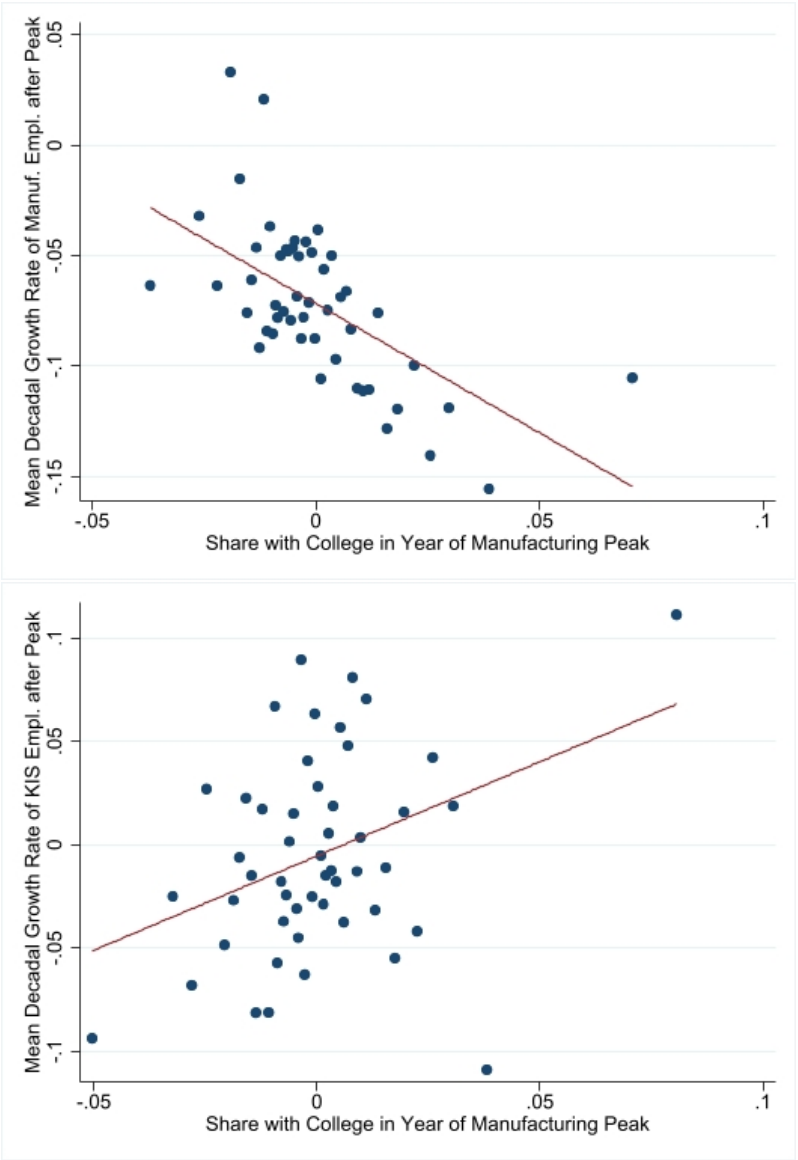
Note: "Top Quartile" includes Local Labor Markets with distance from Colleges or Universities that existed 20 years before the relevant country's manufacturing peak in the top quartile of their country's distribution of distance. The other quartiles are defined similarly. The Figure shows the percent difference between total employment in a given decade and total employment at the time of the manufacturing peak. The change in employment for a given city is computed in deviation from its country's mean. Germany includes only Local Labor Markets in West Germany. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany.

Figure 10: Employment in Human Capital and Knowledge Intensive Services Before and After the Year of Manufacturing Peak, by Quartile of Distance from Historical Colleges



Note: "Top Quartile" includes Local Labor Markets with distance from Colleges or Universities that existed 20 years before the relevant country's manufacturing peak in the top quartile of their country's distribution of distance. The other quartiles are defined similarly. The Figure shows the percent difference between employment in a given decade and employment at the time of the manufacturing peak. The change in employment for a given city is computed in deviation from its country's mean. Data include only United Kingdom and United States.

Figure 11: Share of Local Residents with a College or University Degree in Year of Manufacturing Peak and Change in Employment in Manufacturing and in Human Capital and Knowledge Intensive Services After Manufacturing Peak



Note: Binned scatter plot. The Figure plots the college share in the year of the manufacturing peak on the x-axis and percent decadal employment change in manufacturing (top panel) and human capital and knowledge intensive services (bottom panel) on the y-axis. Both x-axis and y-axis are expressed in deviation from country-level means), controlling for the share of manufacturing at the peak. The solid line shows the best linear fit estimated on the underlying Local Labor Market-level data. Germany includes only Local Labor Markets in West Germany. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany. In the top panel, data include only United Kingdom and United States.

Table 1: Summary Statistics

	(1)	(2)	(3)
	Mean	**Std. Dev.**	**N**
Mean Decadal Growth Rate of Tot. Empl. from Peak to 2010	0.075	0.118	1993
Mean Decadal Growth Rate of Manufact. Empl. from Peak to 2010	-0.070	0.168	1993
Manufact. Share at Peak	0.355	0.161	1993
Total Employment at Peak	77272.26	394005.5	1993
Percent with College Degree at Peak	0.043	0.031	1826
Knowledge Intensive Service Share at Peak	0.116	0.045	477
Mean Growth Rate of KIS Empl. from Peak to 2010	0.478	0.223	477
Mean Growth Rate of non KIS Empl. from Peak to 2010	0.052	0.161	477
Manufact. High-Tech Share at Peak	0.054	0.079	1540
Distance to Nearest Historical College (Km)	108.593	117.978	1888

Mean Decadal Growth Rate of Tot. Empl. from Peak to 2010 is the mean decadal growth rate of total employment between the year of country's manufacturing peak and 2010. Mean Decadal Growth Rate of Manufact. Empl. from Peak to 2010 is the mean decadal growth rate of manufacturing employment between the year of country's manufacturing peak and 2010. Manufact. Share at Peak is the share of LLM's employment in manufacturing in the year of its country's manufacturing peak. Total Employment at Peak is total employment in the year of manufacturing peak. Percent with College Degree at Peak is the share of LLM's residents with at least a college or university degree in the year of country's manufacturing peak. Knowledge-Intensive Service Share at Peak is the share of Human Capital and Knowledge Intensive Service employment in the year of manufacturing peak. Mean Growth Rate of KIS Empl. from Peak to 2010 is the mean decadal growth rate of employment in Human Capital and Knowledge Intensive Services between the year of country's manufacturing peak and 2010. Mean Growth Rate of non KIS Empl. from Peak to 2010 is the mean decadal growth rate of employment in non Human Capital and Knowledge Intensive Services between the year of country's manufacturing peak and 2010. Manufact. High-Tech Share at Peak is the share of high-tech manufacturing employment in the year of manufacturing peak. Distance to Nearest Historical College is the driving distance to the nearest historical research college or university, measured based on colleges and universities that existed 20 years before each country's manufacturing peak. Percent with College Degree at Peak and Distance not available for Japanese LLMs. Manufact. High-Tech Share at Peak not available for French LLMs. Employment in Knowledge Intensive Services available only for UK and US LLMs. The Table reports unweighted means.

Table 2: Summary Statistics, By Country

	(1)	(2)	(3)	(4)	(5)	(6)
	France	**Germany**	**Italy**	**Japan**	**UK**	**USA**
Mean Growth Rate of Tot. Empl. from Peak to 2010	0.072	0.012	0.076	0.035	0.042	0.203
Mean Growth Rate of Manufact. Empl. from Peak to 2010	-0.069	-0.106	-0.057	-0.115	-0.106	-0.023
Manufact. Share at Peak	0.273	0.375	0.398	0.243	0.356	0.33
Total Employment at Peak	44988.79	201508.4	13842.68	440303.6	59220.48	231153.8
Percent with College Degree at Peak	0.061	0.056	0.025	NA	0.048	0.125
Knowledge Intensive Service Share at Peak	NA	NA	NA	NA	0.11	0.128
Mean Growth Rate of KIS Empl. from Peak to 2010	NA	NA	NA	NA	0.466	0.500
Mean Growth Rate of non KIS Empl. from Peak to 2010	NA	NA	NA	NA	-0.009	0.164
Manufact. High-Tech Share at Peak	NA	0.134	0.027	NA	0.091	0.093
Distance to Nearest Historical College (Km)	272.21	52.12	90.41	NA	52.35	12.77

Mean Growth Rate of Tot. Empl. from Peak to 2010 is the mean decadal growth rate of total employment between the year of country's manufacturing peak and 2010. Mean Growth Rate of Manufact. Empl. from Peak to 2010 is the mean decadal growth rate of manufacturing employment between the year of country's manufacturing peak and 2010. Manufact. Share at Peak is the share of LLM's employment in manufacturing in the year of its country's manufacturing peak. Total Employment at Peak is total employment in the year of manufacturing peak. Percent with College Degree at Peak is the share of LLM's residents with at least a college or university degree in the year of country's manufacturing peak. Knowledge-Intensive Service Share at Peak is the share of Human Capital and Knowledge Intensive Service employment in the year of manufacturing peak. Mean Growth Rate of KIS Empl. from Peak to 2010 is the mean decadal growth rate of employment in Human Capital and Knowledge Intensive Services between the year of country's manufacturing peak and 2010. Mean Growth Rate of non KIS Empl. from Peak to 2010 is the mean decadal growth rate of employment in non Human Capital and Knowledge Intensive Services between the year of country's manufacturing peak and 2010. Manufact. High-Tech Share at Peak is the share of high-tech manufacturing employment in the year of manufacturing peak. Distance to Nearest Historical College (Km) is the driving distance to the nearest historical research college or university, measured based on colleges and universities that existed 20 years before each country's manufacturing peak. Percent with College Degree at Peak and Distance not available for Japanese LLMs. Manufact. High-Tech Share at Peak not available for French LLMs. Employment in Knowledge Intensive Services available only for UK and US LLMs. The Table reports unweighted means.

Table 3: Share of a Country's Local Labor Markets with Positive Relative Growth and Geographical Variation in Mean Decadal Growth Rate of Total Employment after Peak of Manufacturing – Sample of Manufacturing Hubs

	(1)	(2)	(3)	(4)
	Percent With Relative Growth >0	**p90–p10**	**p75–p25**	**Std. Deviation**
All Countries	0.341	0.212	0.117	0.089
France	0.303	0.159	0.085	0.063
Germany	0.472	0.177	0.079	0.061
Italy	0.388	0.211	0.114	0.085
Japan	0.361	0.167	0.100	0.104
UK	0.283	0.229	0.130	0.094
USA	0.172	0.234	0.115	0.086

The sample includes former manufacturing hubs, defined as cities that in the year of their country's manufacturing peak had a local manufacturing employment share in the top tercile. Cities with positive relative growth are cities that in the period between their country's manufacturing peak and 2010 have gained employment relative to their country mean. Germany includes only Local Labor Markets in West Germany.

Table 4: Share of Local Labor Markets with Positive Relative Growth – Alternative Definitions of Manufacturing Hubs

	(1)	(2)	(3)
	Top Tercile Manuf Share	**Top 25 percent Manuf Share**	**Top 10 percent Manuf Share**
All Countries	0.341	0.329	0.309
France	0.303	0.305	0.276
Germany	0.472	0.424	0.333
Italy	0.388	0.369	0.372
Japan	0.361	0.355	0.346
UK	0.283	0.283	0.234
USA	0.172	0.157	0.119

Column 1 includes only former manufacturing hubs are defined as Local Labor Markets that in the year of their country's manufacturing peak have a manufacturing employment share in the top tercile of the country distribution. Columns 2 and 3 include Local Labor Markets that in the year of their country's manufacturing peak have a manufacturing employment share in the top quartile of the country distribution (column 2); or in the top 10% of their country distribution (column 3). Germany includes only Local Labor Markets in West Germany.

Table 5: Examples of Former Manufacturing Hubs With Relative Employment Declines and Relative Employment Gains

		Manufact. Share in Year of Country's Manufact. Peak	Mean Decadal Growth Rate of Total Employment After Peak of Manufact. (deviation from country mean)
		(1)	(2)
France	Dunkerque	0.39	-0.06
	Compiegne	0.38	0.03
Germany	Wuppertal	0.46	-0.14
	Erlangen	0.47	0.07
Italy	Udine	0.43	-0.03
	Padua	0.44	0.07
Japan	Ashikaga	0.44	-0.11
	Anjo	0.46	0.06
UK	Middlesbrough	0.44	-0.17
	Slough	0.44	0.08
USA	Toledo, OH	0.39	-0.13
	Columbus, OH	0.35	0.01

Mean decadal growth rate of total employment is calculated from the year of manufacturing peak to 2010.

Table 6: Effect of Initial Share of College-Educated Workers on Subsequent Employment Growth

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Share	1.02***	1.13***	1.23***	1.22***	1.27**	1.46**	2.43**	2.95***
	(0.13)	(0.13)	(0.14)	(0.18)	(0.57)	(0.62)	(1.08)	(0.88)
Manuf Share	-0.15***	-0.14***	-0.14***	-0.13***	-0.14***	-0.14***	-0.11***	-0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Coeff on College Share equal to OLS (p-value)					0.6593	0.5944	0.2724	0.0548
First Stage								
Log Distance					-0.0048***	-0.0044***	-0.0028***	-0.0042***
					(0.0007)	(0.0007)	(0.0007)	(0.0008)
AP F-statistics					47.67	40.85	15.09	30.41
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total Empl		Yes	Yes	Yes		Yes	Yes	Yes
Urban			Yes	Yes			Yes	Yes
High Tech Share				Yes				Yes
N	1826	1826	1826	1478	1826	1826	1826	1478

The dependent variable is the Mean decadal growth rate of Total Employment. Robust standard errors in parentheses. AP 1st stage F-statistics: Angrist-Pischke multivariate test of excluded instruments F-statistic. % High-Tech MF not available for French cities. Germany includes only Local Labor Markets in West Germany. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of Initial Share of College-Educated Workers on Subsequent Employment Growth – IV Measured Further Back in Time

When Distance is Measured:	20 Years Before Peak	30 Years Before Peak	40 Years Before Peak	50 Years Before Peak
	(1)	(2)	(3)	(4)
College Share	2.95***	2.60***	2.63***	2.54***
	(0.88)	(0.88)	(0.88)	(0.83)
Manuf Share	-0.09***	-0.10***	-0.09***	-0.10***
	(0.03)	(0.03)	(0.03)	(0.03)
Coeff on College Share equal to col 1 (p-value)		0.2880	0.3260	0.2516
First Stage				
Log Distance	-0.0042***	-0.0041***	-0.0041***	-0.0042***
	(0.0008)	(0.0008)	(0.0008)	(0.0007)
AP F-statistic	30.41	28.37	28.63	32.07
Country FE	Yes	Yes	Yes	Yes
Total Empl	Yes	Yes	Yes	Yes
Urban	Yes	Yes	Yes	Yes
High Tech Share	Yes	Yes	Yes	Yes
N	1478	1478	1478	1478

The dependent variable is the mean decadal growth rate of Total Employment. Robust standard errors in parentheses. AP 1st stage F-statistics: Angrist-Pischke multivariate test of excluded instruments F-statistic. Germany includes only Local Labor Markets in West Germany. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of Initial Share of College-Educated Workers on Subsequent Manufacturing Employment Growth

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
College Share	-1.23***	-1.00***	-0.70***	-0.84**	-2.67***	-2.45**	-1.28	-0.98
	(0.24)	(0.25)	(0.25)	(0.36)	(0.92)	(0.97)	(1.51)	(1.16)
Manuf Share	-0.33***	-0.31***	-0.31***	-0.28***	-0.36***	-0.35***	-0.32***	-0.28***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)
First Stage								
Log Distance					-0.0048***	-0.0044***	-0.0028***	-0.0042***
					(0.0007)	(0.0007)	(0.0007)	(0.0008)
AP F-statistics					47.67	40.85	15.09	30.41
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total Empl		Yes	Yes	Yes		Yes	Yes	Yes
Urban			Yes	Yes			Yes	Yes
High Tech Share				Yes				Yes
N	1826	1826	1826	1478	1826	1826	1826	1478

The dependent variable is the Mean decadal growth rate of Manufacturing Employment. Robust standard errors in parentheses. AP 1st stage F-statistics: Angrist-Pischke multivariate test of excluded instruments F-statistic. % High-Tech MF not available for French cities. Germany includes only Local Labor Markets in West Germany. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

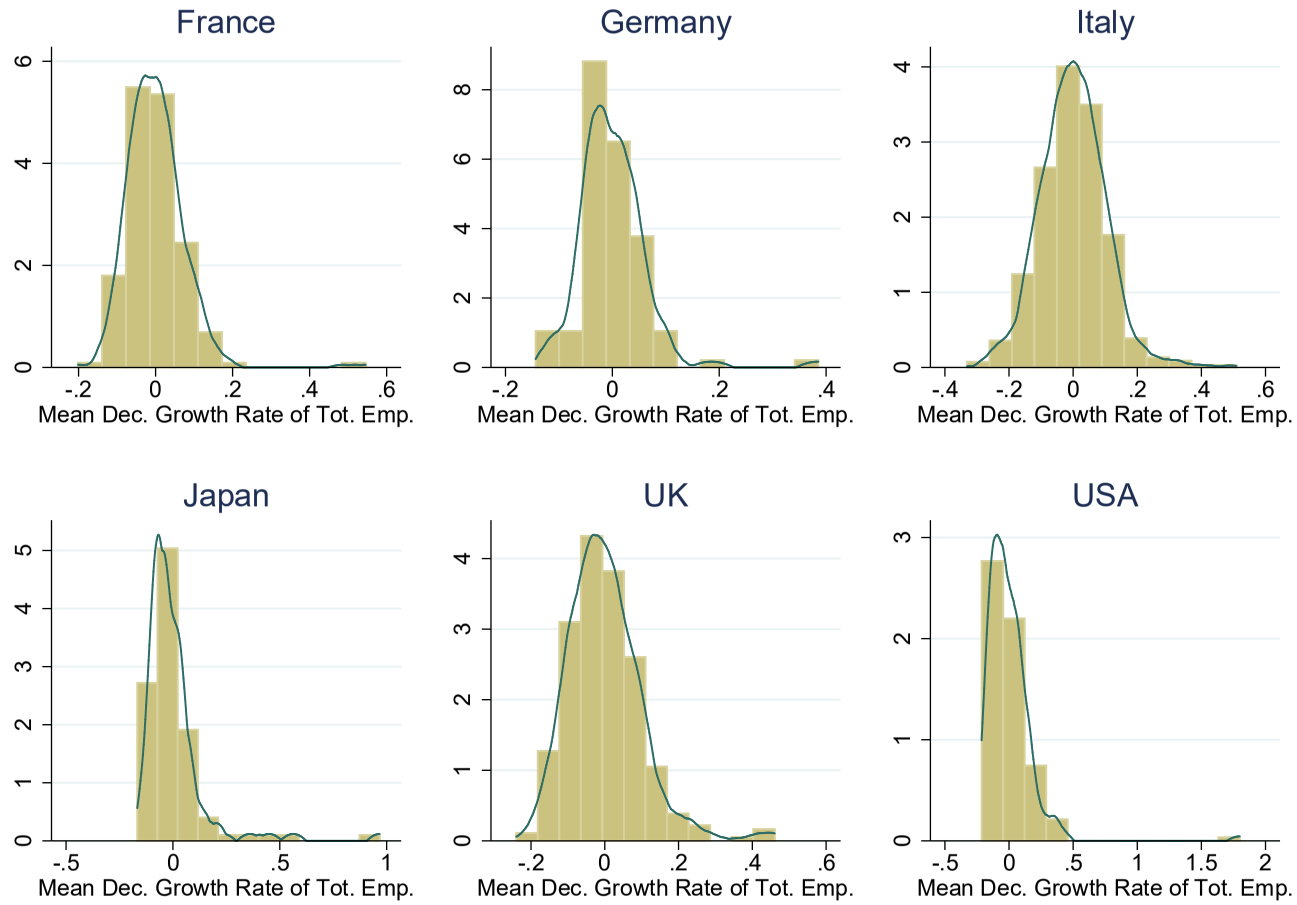
Table 9: Effect of Initial Share of College-Educated Workers on Subsequent Employment Growth in Knowledge Intensive Services and Non-Knowledge Intensive Services

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: **Knowledge Intensive Services**								
College Share	1.01***	1.18***	1.18***	1.30***	3.54*	3.49*	3.49*	4.33*
	(0.32)	(0.31)	(0.31)	(0.33)	(2.03)	(1.96)	(2.01)	(2.58)
Manuf Share	-0.06	-0.03	-0.03	-0.02	0.05	0.08	0.08	0.13
	(0.05)	(0.05)	(0.05)	(0.05)	(0.10)	(0.10)	(0.11)	(0.14)
First Stage								
Log Distance					-0.0033***	-0.0033***	-0.0036***	-0.0030**
					(0.0012)	(0.0012)	(0.0013)	(0.0013)
AP F-statistics					7.31	7.50	7.21	5.29
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total Empl		Yes	Yes	Yes		Yes	Yes	Yes
Urban			Yes	Yes			Yes	Yes
High Tech Share				Yes				Yes
N	408	408	408	408	408	408	408	408
Panel B: **Non-Knowledge Intensive Services**								
College Share	0.61***	0.76***	0.77***	0.80***	0.02	0.01	1.23	1.45
	(0.23)	(0.23)	(0.23)	(0.23)	(1.43)	(1.39)	(1.36)	(1.67)
Manuf Share	-0.34***	-0.31***	-0.30***	-0.30***	-0.36***	-0.35***	-0.28***	-0.27***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)	(0.07)	(0.09)
First Stage								
Log Distance					-0.0030**	-0.0030**	-0.0033**	-0.0027**
					(0.0012)	(0.0012)	(0.0013)	(0.0013)
AP F-statistics					6.29	6.39	6.32	4.52
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total Empl		Yes	Yes	Yes		Yes	Yes	Yes
Urban			Yes	Yes			Yes	Yes
High Tech Share				Yes				Yes
N	408	408	408	408	408	408	408	408

Dependent variable: mean decadal growth rate of Employment in Knowledge Intensive Services (Panel A) and mean decadal growth rate of Employment in Non-Knowledge Intensive Services (Panel B). Data includes only United Kingdom and United States trimmed 1-99 percentiles. AP 1st stage F: Angrist-Pischke multivariate test of excluded instruments F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

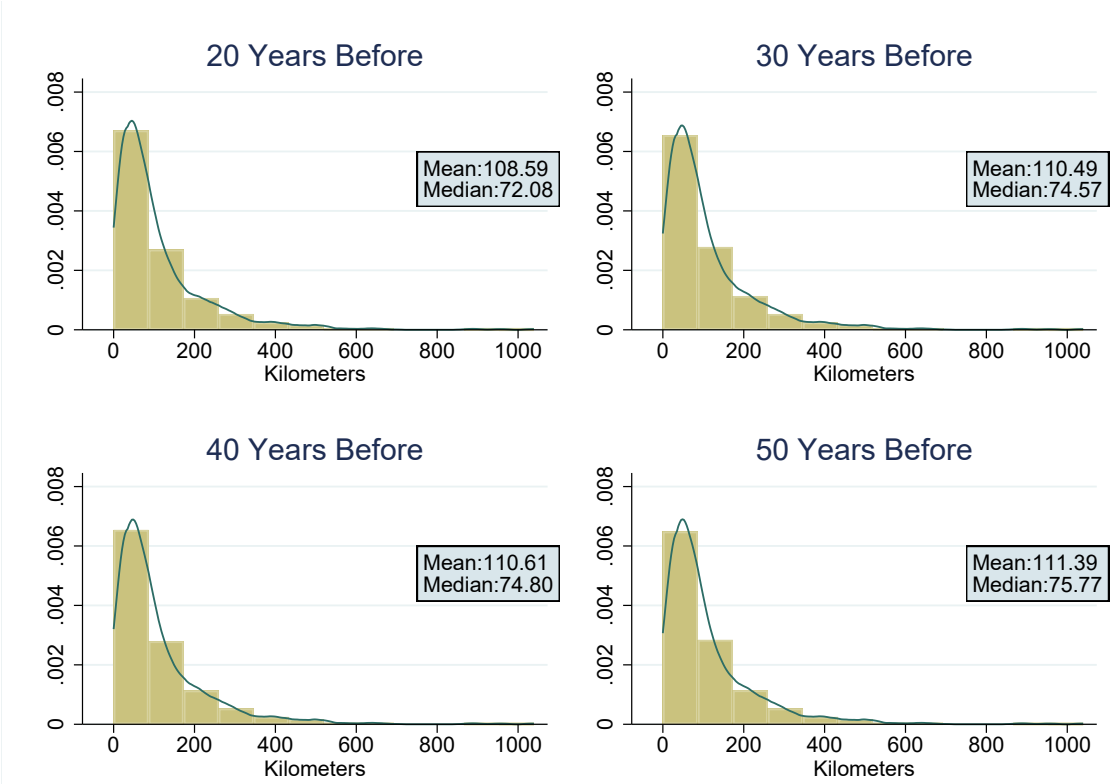
A Appendix

Figure A.1: Spatial Distribution of Mean Decadal Growth Rate of Total Employment After Peak of Manufacturing – All Cities



Note: The city-level mean decadal growth rate of total employment after manufacturing peak is expressed in deviation from the country-level mean decadal growth rate. Germany includes only Local Labor Markets in West Germany.

Figure A.2: Distribution of Driving Distance to Nearest Historical College or University



Distance is measured based on Colleges and Universities that existed 20, 30, 40 or 50 years before each country's manufacturing peak. Germany includes only Local Labor Markets in West Germany. The peak year of manufacturing employment is 1970 for the United Kingdom and United States; 1980 for France and Italy; and 1990 for Germany.

Table A.1: Effect of Initial Share of College-educated Workers on Subsequent Employment Growth in Models that Include the Interaction between College Share and a Dummy for Former Manufacturing Hubs

	OLS	IV	N
Panel A: **Total Employment**			
College Share	1.26***	2.90***	1478
	(0.18)	(0.85)	
College Share*Manuf Hub	-0.39***	-0.48***	1478
	(0.14)	(0.18)	
Sum of the two Coefficitents equal to 0 (p-value)	0.0001	0.0023	
Panel B: **Manufacturing**			
College Share	-0.82**	-1.01	1478
	(0.36)	(1.15)	
College Share*Manuf Hub	-0.25	-0.24	1478
	(0.21)	(0.22)	
Sum of the two Coefficitents equal to 0 (p-value)	0.0020	0.2505	
Panel C: **Human Capital and Knowledge Intensive Services**			
College Share	1.39***	4.19*	408
	(0.34)	(2.43)	
College Share*Manuf Hub	-0.37	-0.76*	408
	(0.24)	(0.44)	
Sum of the two Coefficitents equal to 0 (p-value)	0.0068	0.1036	

The dependent variable is the Mean decadal growth rate of Total Employment (Panel A)/ Manufacturing Employment (Panel B)/ Knowledge Intensive Services Employment (Panel C). Robust standard errors in parentheses. The table shows the results of Columns 4 and 8 in Table 6, 8 and 9 with the inclusion of the interaction between college share and an identifier for former manufacturing hubs. Other controls include Manufacturing Share, Total Employment, Country FE, Urban, and High Tech Share. Manufacturing hubs are defined as cities that in the year of their country's manufacturing peak had a local manufacturing employment share in the top tercile. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.