The London School of Economics and Political Science

Essays on Skills, Management and Productivity

Anna Sivropoulos-Valero

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of 49,391 words (as calculated by texcount utility in Overleaf).

London, 18th July 2018

Anna Sivropoulos-Valero

Statement of conjoint work

I confirm that Chapter 1, ***"The Economic Impact of Universities: Evidence from Across the Globe"***, was jointly co-authored with Professor John Van Reenen. A previous version of this paper has been published as CEP Discussion Paper No 1444 (August 2016, revised January 2018) and NBER Working Paper No. 22501 (August 2016). After submission of this thesis in July 2018, this paper was accepted for publication at the *Economics of Education Review*. This statement is to confirm that I contributed 50 per cent of this work.

I confirm that Chapter 3, ***"Skill Biased Management: Evidence from Manufacturing Firms"***, was jointly co-authored with Andy Feng. This paper is the result of merging our two related but previously separate papers. My original work, which built significantly on my MRes paper, "Skill-Biased Management: Evidence from European Manufacturing Firms" (2011), focused on relating firm management practices to measures of regional skills and regional skill premia (based on international labour force data) and university presence. Andy Feng's original paper, "Human Capital and Management Practices: Evidence from Driving Times to Universities", was Chapter 2 of his 2013 thesis, "Human Capital and Management Practices" (http://etheses.lse.ac.uk/id/eprint/787). This paper analysed the relationship between firm management practices and distance to closest university. This statement is to confirm that I contributed 50 per cent of the work in this merged paper. This includes my original analysis, together with updating all analysis for consistency, extending it in places, and drafting this latest version of the paper.

I confirm that Chapter 4, ***"Industry in Britain: An Atlas"***, was jointly co-authored with Sandra Bernick and Richard Davies. This paper has been published as a CEP Special Paper No 34 (September 2017). This statement is to confirm that I contributed 33 per cent of this work.

Anna Sivropoulos-Valero

Disclaimers

Chapter 2, ***"The Local Economic Impact of Universities: Evidence from UK firms"***, makes use of confidential data collected by the UK Office for National Statistics and securely provided by the UK Data Service. The following disclaimer applies: This work contains statistical data from the ONS, which is Crown Copyright. The use of ONS statistical data does not imply the endorsement of the ONS in relation to the interpretation or analysis of the data. This work uses research datasets, which may not exactly reproduce National Statistics aggregates.

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I dedicate this PhD to my daughters Sofia and Alexia, the lights of my life, who have brought me joy, purpose and perspective, and who I hope will grow up remembering that in life the journey - and what we learn from it - is more important than the destination.

Abstract

This thesis investigates the role of skills and universities in explaining differences in economic performance between firms and regions. The first chapter examines the relationship between university entry and GDP growth between 1950 and 2010 based on new data that combines university entry in 1,500 regions across 78 countries. It finds that a 10% increase in a region's universities is associated with 0.4% higher GDP per capita in that region, with evidence of spillovers to neighbouring regions. Part of the university effect appears to be mediated through increases in human capital and innovation, and we also find evidence that universities shape views on democracy.

Focusing on the UK, the second chapter studies how university growth impacts on local industry composition and productivity using panel data on firms and nearby university enrolments over the period 1997-2016. This spatial analysis reveals that university growth stimulates high-tech start-ups and the effects are stronger for higher quality, research intensive universities and areas of higher initial human capital. Employment effects are more muted, though smaller establishments appear to get larger as universities grow. On average, positive productivity impacts are found only in more high-tech intensive areas.

The third chapter provides evidence for a complementarity between modern management practices and higher education using data on manufacturing firms, universities and labour markets across 19 countries. It finds that firms further from universities have lower management scores, even when controlling for a rich set of observables and region fixed effects. Analysis using estimates of regional skill premia suggests that variation in the price of skills drives these effects.

The fourth chapter examines differences in economic performance across the UK using a variety of data sources and measures. Ten stylised facts are presented which are relevant for policymakers and researchers engaged in the development of industrial strategy in the UK.

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Chapter 1

The Economic Impact of Universities: Evidence from Across the Globe[1]

[1] We would like to thank Andy Feng, Sandra McNally, Henry Overman, Katheryn Shaw, Andrei Shleifer and participants at seminars at the CEP, LSE, MIT, RES Conference and HM Treasury for helpful comments. Nicola Gennaioli, Rafael La Porta and Florencio Lopez De Silanes were kind enough to make their regional data available to us. Financial support from the ESRC through the CEP is gratefully acknowledged.

1.1 Introduction

A striking feature of the last hundred years has been the enormous expansion in university education. In 1900, only about one in a hundred young people in the world were enrolled at universities, but over the course of the Twentieth Century this rose to about one in five (Schofer and Meyer, 2005). The term "university" was coined by the University of Bologna, founded in 1088, the first of the medieval universities. These were communities with administrative autonomy, courses of study, publicly recognised degrees and research objectives and were distinct from the religion-based institutions that came before (De Ridder-Symoens and Rüegg, 1992). Since then, universities have spread worldwide in broadly the same form, and it has been argued that they were an important force in the Commercial Revolution through the development of legal institutions (Cantoni and Yuchtman, 2014) and the industrial revolution through their role in the building of knowledge and its dissemination (Mokyr, 2002).

While there is an extensive literature on human capital and growth, there is relatively little research on the economic impact of universities themselves. In this paper, we develop a new dataset using the World Higher Education Database (WHED) that contains the location of universities in 1,500 regions across 78 countries in the period since World War II (when consistent sub-national economic data are available). We focus on how university formation is correlated with future economic growth. Over this period university expansion accelerated in most countries; a trend partially driven by the view that higher education is essential for economic and social progress. This was in contrast to the pre-War fears of "over-education" that were prevalent in many countries, should enrolments much extend beyond the national elites (Schofer and Meyer, 2005; Goldin and Katz, 2008).

There are a number of channels through which universities may affect growth including (i) a greater supply of human capital; (ii) more innovation; (iii) support for democratic values; and (iv) demand effects. Firstly, and most obviously, universities are producers of human capital; and skilled workers are more productive than unskilled workers. Geographical distance seems to matter as areas with better university access benefit both from improving the chances that locally born young people will attend college (e.g. Card (2001)) and also because students who graduate are more likely to seek work in the area where the university is located. The empirical macro literature has generally found that at the country level, human capital (typically measured by years of schooling) is important for development and growth (e.g. Sianesi and Van Reenen (2003)). Growth accounting and development accounting relate educational attainment to economic performance and find a non-trivial contribution.[2] Explicit econometric analysis usually, although not always, confirms this positive relationship.[3]

A problem with these empirical studies is that they are at the country level and subject to the concern that there are omitted aggregate variables (e.g. Bils and Klenow (2000); Hanushek and Woessmann (2009)). At the sub-national level, Gennaioli et al. (2013) show that *regional* years of schooling is important for *regional* GDP per capita in the cross section and Gennaioli et al. (2014) confirm this relationship also holds for growth regressions. Furthermore, human capital appears to also have an indirect effect via spillovers which are analysed *inter alia* by Moretti (2004*a*) at the firm level and Moretti (2004*b*) and Glaeser and Lu (2018) at the individual level. In an historical setting, Squicciarini and Voigtländer (2014) show that "upper tail" knowledge was important in the industrial revolution, and they measure this type of knowledge using city level subscriptions to the Encyclopédie in mid-18th century France.

A second channel through which universities may affect growth is innovation. This may be an indirect influence because, as in the previous point, universities increase educational supply.[4] But it could also be a direct influence as university researchers themselves produce innovations, sometimes in collaboration with local firms. A number of empirical papers have found that universities increase local innovative capacity.[5] A drawback of this literature is that it uses proxies for innovation such as patents rather than looking at economic output directly. Moreover, the work is also focused on single countries, somewhat limiting its generalisability.

A third way universities may matter is by fostering pro-growth institutions. Universities could promote strong institutions directly by providing a platform for democratic dialogue and sharing of ideas, through events, publications, or reports to policy makers. A more obvious channel would be that universities strengthen institutions via their role as human capital producers. The relationship between human capital, institutions and

[2] For example, Mankiw, Romer and Weil (1992), Hall and Jones (1999) and Caselli (2005).

[3] For example, Barro (1991), de La Fuente Angel and Domenech (2006) and Cohen and Soto (2007).

[4] This may be wider than just via technology, Feng and Valero (2018) and Bloom et al. (2017) also find a role for universities in helping diffuse productivity-enhancing managerial best practices.

[5] This literature stems from Jaffe (1989) who uses US state level data to provide evidence of spillovers from university research to patenting and R&D spending by firms. A number of papers have shown that such effects are localised (see for example, Jaffe, Trajtenberg and Henderson (1993), Anselin, Varga and Acs (1997), Fischer and Varga (2003), Belenzon and Schankerman (2013)). Andrews (2017) exploits quasi random allocation of universities to US counties over the period 1839-1954 to estimate their causal impact on patenting. Toivanen and Väänänen (2016) consider how universities affect innovation via their role as human capital producers: they use distance to a technical university as an instrument in estimating the effect of engineering education on patents in Finland (which they find to be positive and significant).

growth are much debated in the literature. Indeed, there remains controversy over whether institutions matter at all for growth.[6] Some papers have argued that human capital is the basic source of growth, and the driver of democracy and improved institutions (e.g. Glaeser et al. (2004)). But the relationship between education and democracy/institutions is contested by Acemoglu et al. (2005) who argue that the effects found in the cross section of countries are not robust to including country fixed effects and exploiting within-country variation.

Finally, universities may affect growth through a more mechanical "demand" channel. Increased consumption from students and staff and the universities' purchase of local goods and services could have a material impact on GDP. This would occur when a new university attracts new students and staff into the region, or when university costs are financed though national governments from tax revenues raised mainly outside the region where the university is located.

We show that university growth has a strong association with later GDP per capita growth at the sub-national level. Even after including a host of controls (including country or region fixed effects to control for differential regional trends, and year dummies) we find that a 10% increase in the number of universities in a region is associated with about 0.4% higher GDP per capita. We show that reverse causality does not appear to be driving this, nor do demand effects. We also find that increases in universities in neighbouring regions is also correlated with a region's growth. Finally, we show that the association of per capita GDP and university presence works partially through increasing the supply of human capital and also through raising innovation, but both these channels appear to be small in magnitude. In addition, in the cross sectional analysis we find that universities appear to be correlated with more pro-democratic views even when we control for human capital, consistent with a story that they may have some role in shaping institutions over longer time horizons.

If policy-makers decided to open new universities in areas with strong economic potential, any positive correlation could simply be due to expectations of growth causing university formation rather than vice versa. Our view is that in the post-war period, university expansion was largely a policy pursued by national governments rather than simply a response to local sub-national conditions. Governments were focused on social equity (Dahrendorf, 1965), improving technological capacity (in response to the Cold War,

[6] See, for example, Acemoglu, Robinson and Johnson (2005) and Acemoglu et al. (2014) who argue institutions matter a lot, and Gerring et al. (2005) for a summary of papers that conclude that they do not.

especially the 1957 Sputnik crisis (Barr, 2014)) and a general recognition of the value of human capital (Becker, 1964). This kind of "development planning" (Schofer and Meyer, 2005) stood in contrast to pre-war period views which often saw little need to extend tertiary education beyond a narrow elite.

In the Appendix (1.A.4) we describe three country case studies of largescale university expansion which all have a substantial exogenous element to local economic conditions. Nonetheless, we attempt to address endogeneity concerns by using lagged university openings, controlling for a rich set of observables and including both unobserved regional fixed effects and regional trends in the regressions. We do not have credible external instrumental variables to rule out all possibilities of endogeneity bias. In particular, time varying unobservables at the region level cannot be controlled for in this framework. If, for example, some regional policy-makers opened new universities and also pursued other growth enhancing policies, the reported association might emerge without a causal effect of universities on growth. The strength of our analysis is in the comprehensiveness of the new data across space and time and the associations we document should be seen as suggestive rather than definitive.

To date, few papers have explicitly considered the direct link between university presence and economic performance. Cantoni and Yuchtman (2014) argue that medieval universities in 14$^{\text{th}}$ century Germany played a causal role in the commercial revolution (using distance from universities following the Papal Schism, an exogenous event which led to the founding of new universities in Germany). In a contemporary setting, Hausman (2017) links university innovation to economic outcomes in US counties, finding that long-run employment and pay rises in sectors closely tied with a local university's innovative strength, and that this impact increases in proximity to university. Aghion et al. (2009) consider the impact of research university activity on US states. Using political instruments, they find that exogenous increases in investments in four year college education affect growth and patenting. Kantor and Whalley (2014) estimate local agglomeration spillovers from US research university activity, using university endowment values and stock market shocks as an instrument for university research spending. They find evidence for local spillover effects to firms, which is larger for research intensive universities or firms that are "technologically closer" to universities.[7] Feng and Valero (2018) use international data

[7] In related work, Kantor and Whalley (2016) find evidence of agricultural productivity effects from proximity to research in US agricultural research stations. Effects appear persistent where stations focused on basic research and farmers were already at the technology frontier.

to show that firms that are closer to universities have better management practices (Bloom, Sadun and Van Reenen, 2017).

This paper is organised as follows. Section 1.2 describes the data and some of its key features including interesting trends and correlations which give us a macro level understanding of the global rise in universities over time. Section 1.3 sets out our econometric strategy, and Section 1.4 our results. Section 1.5 explores the mechanisms through which universities appear to affect regional growth and finally, Section 1.6 provides some concluding comments.

1.2 Data

Our regression analysis is based upon information on universities in some 1,500 regions in 78 countries. This represents the set of regions for which our university data can be mapped to a regional time series of key economic variables obtained from Gennaioli et al. (2014), and covers over 90 per cent of global GDP.[8] We first describe the full World Higher Education Database (WHED) across all countries, with some key global trends and correlations. Then we focus on the 78 countries for which regional economic data are available, describing how we aggregate the WHED data into regions, and present some initial descriptive evidence.

1.2.1 World Higher Education Database

WHED is an online database published by the International Association of Universities in collaboration with UNESCO.[9] It contains information on higher education institutions that offer at least a three year or more professional diploma or a post-graduate degree. In 2010, there were 16,326 universities across 185 countries meeting this criterion. The database therefore excludes, for example, community colleges in the US and further education institutions in the UK and may be thought of as a sample of "higher quality" universities. Key variables of interest include university location, founding date, subjects and qualifications offered and other institutional details such as how they are funded.

Our regional analysis is based on that sample of countries for which GDP and other data are available from 1955, which covers 78 countries, comprising 14,868 (or 91%) of the institutions from the full listing. Our baseline results simply use the year-specific count of

[8] Based on World Bank GDP in 2014 (US dollars, PPP).
[9] For more information, see http://www.whed.net/home.php.

universities by region as a measure of university presence, always controlling for regional population. To calculate this, we first allocate each university to a region (for example, a US state), and then use the founding dates of universities in each region to determine the number of universities that were present at any particular date.[10] High rates of university exit would invalidate this type of approach, but we find that this does not appear to be an issue over the decades since the 1950s (see the Data Appendix 1.A).

A disadvantage of the "university density" measure is that it does not correct for the size or quality of the university. Unfortunately, this type of data is not available on a consistent basis across all countries over time, but we present robustness results on a sub-sample where we do have finer grained measures of university size, and use various measures of university type as proxies for quality.

1.2.2 The Worldwide Diffusion of Universities

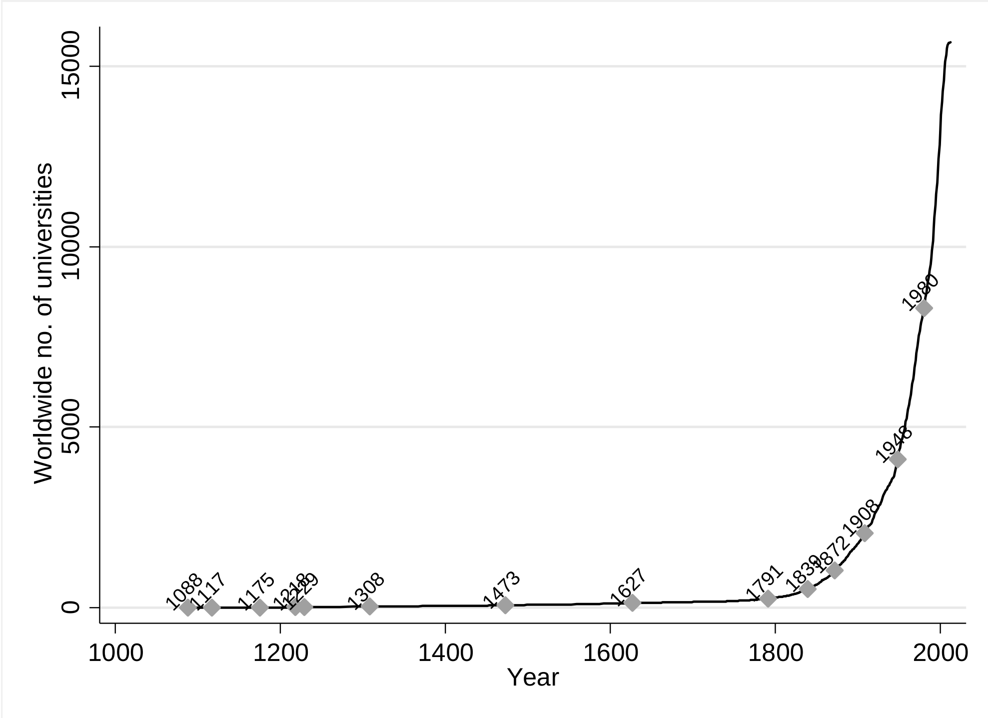
We begin by presenting some descriptive analysis of the university data at the macro level using the full university database. Figure 1.2.1 shows how the total number of universities has evolved over time; marking the years that the number doubled. The world's first university opened in 1088 (in Bologna) and growth took off in the 19th Century, growing most rapidly in the post-World War II period (see Panel A). In Panel B we normalise the number of worldwide universities by the global population to show that university density also rose sharply in the 1800s. It continued to rise in the 20th Century, albeit at a slower rate and has accelerated again after the 1980s when emerging countries like Brazil and India saw rapid expansions.

A number of additional descriptive charts are in the Appendix. The distribution of universities across countries is skewed, with seven countries (US, Brazil, Mexico, Philippines, Japan, Russia and India, in descending order) accounting for over half of the universities in the world in 2010 (the US accounts for 13% of the world's universities). We also examine the "extensive margin" – the cumulative number of countries that have any university over time with Bhutan being the latest country to open a university in 2003. By 2010, the vast majority of countries in the world had at least one university. We also provide an historical overview of the diffusion of universities from the 1880s in four advanced economies: France, Germany, the UK and US, and two emerging economies:

[10] Of the full sample of 16,326 universities, we were unable to obtain founding date information for 669 institutions (4% of the total). 609 of these fall into our core analysis sample (in the 78 countries for which regional economic data are available). These institutions are therefore omitted from analysis.

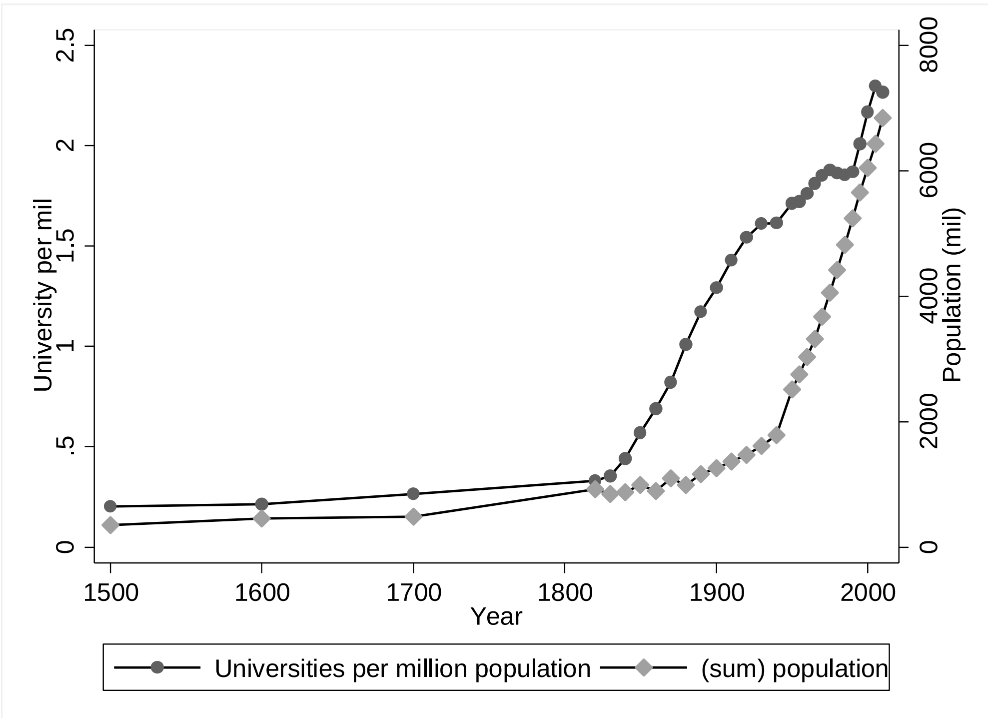
Figure 1.2.1: Worldwide Universities Over Time

A: University Count



NOTES: The evolution of global universities over time; years where the total number doubled are marked. Source: WHED.

B: University Density and Population



NOTES: This chart shows the evolution of global university density (universities per million people) and population over time. Source: WHED and Maddison population data.

India and China at the country level. We compare the timing of historical university expansions to growth and industrialisation. Descriptively, the data looks broadly in line with the thesis of Mokyr (2002) that the building and dissemination of knowledge played an important role in the industrialisation of many countries.

For further description of the data at the national level, we examine the cross sectional correlations of universities with key economic variables. Unsurprisingly, we find that higher university density is associated with higher GDP per capita levels. It is interesting that countries with more universities in 1960 generally had higher growth rates over the next four decades. Furthermore, there are strong correlations between universities and average years of schooling, patent applications and democracy.[11] These correlations provide a basis for us to explore further whether universities matter for GDP growth within countries, and to what extent any effect operates via human capital, innovation or institutions.

1.2.3 Regional Economic Data

We obtain regional economic data from Gennaioli et al. (2014) who collated key economic variables for growth regressions at the sub-national level.[12] The outcome variable we focus on is regional GDP per capita. Since for many countries, regional GDP data and other variables such as population or years of education are not available annually we follow Barro (2012) and compute average annual growth rates in GDP per capita over five year periods.[13] We also gather patents data at the regional level as a measure of innovation. For 38 countries, we obtain region-level European Patent Office (EPO) patents from the OECD REGPAT database covering 1978 to 2010.

Table 1.2.1 has some descriptive statistics of our sample of 8,128 region-years. The average region has GDP per capita of just over $13,000, average growth of 2% per annum and nearly ten universities (this is quite skewed with a median of 2, so in our robustness tests, we show that our results are not sensitive to dropping region-years with no universities).[14]

[11] We use Polity scores as a measure of democracy, as is common in the literature. See for example Acemoglu et al. (2014).

[12] The availability of regional data for different countries is outlined in Gennaioli et al. (2014).

[13] We interpolate missing years, but do not extrapolate beyond the final year (or before the first year of data). Our results are robust to dropping interpolated data.

[14] A related fact is that the median growth rate of the number of universities is zero (5,856 observations). This implies that 28 per cent of the observations have an increase in the number of universities. We also checked that the results are not driven by regions that increased their number of universities from zero to one or more.

Table 1.2.1: Descriptive Statistics

	Mean	S.D	Min	p50	Max	Obs
Regional GDP per capita	13,055.75	11,958.30	262.15	8,463.02	105,648.25	8,128
Growth in regional GDP pc	0.02	0.03	-0.20	0.02	0.30	8,128
Country GDP per capita	14,094.16	11,525.30	690.66	9,157.66	64,198.29	8,128
# universities	9.60	23.71	0	2.00	461.00	8,128
Growth in # universities	0.02	0.03	0	0.0	0.28	8,128
Population (millions)	2.78	7.97	0.01	1.01	196.00	8,128
Growth in population	0.01	0.02	-0.14	0.01	0.25	8,128
Latitude	27.74	25.65	-54.33	37.75	69.95	8,128
Inverse dist. to ocean	0.03	0.07	0	0.01	1.89	8,128
Malaria index	0.89	2.31	0	0.01	25.51	8,128
log(oil and gas production)	1.72	2.86	0	0.00	12.05	8,128
Dummy for capital in region	0.05	0.22	0	0	1.00	8,128
Dist. to nearest region ('000km)	0.14	0.19	0.01	0.08	2.79	8,128
College share	0.07	0.07	0.00	0.04	0.45	5,744
Years of education	7.37	3.08	0.39	7.42	13.76	6,640

NOTES: Each observation is region-year. Source: WHED and Gennaioli et al. (2014) for regional economic data. Oil and gas production refers to the period 1950-2010.

As we set out in the next section, our core regressions will control for the level and growth of population[15], and a number of geographic characteristics – including an indicator for whether a region contains a country's capital. Measures of regional human capital (college share and years of education) are available for sub-samples of region-years. People in the average region have an average of seven years of education with just seven percent of them having attended college.

Figure 1.2.2 shows that the raw correlations between growth rates of universities and GDP per capita that we saw at the country level are also present within countries. Panel A simply plots the average annual growth in regional GDP per capita (on the y-axis) on the average annual growth in universities (on the y-axis), over the whole time period for which data are available (which differs by region). Average GDP per capita growth rates are plotted within 20 evenly sized bins of university growth, and country fixed effects are absorbed so that variation is within country. Panel B plots GDP per capita growth rates on lagged university growth for the 8,128 region-years (on which we conduct the core of our analysis that will follow). In both graphs it is clear that there is a positive relationship.[16]

1.3 Empirical Framework

The underlying model we are interested in is the long-run relationship between universities and economic performance:

$$ln(Y/L_{ic,t}) = \alpha_1 ln(Uni_{ic,t}) + \alpha_2 ln(Pop_{ic,t}) \tag{1.3.1}$$

where $Y/L_{ic,t}$ is the level of GDP per capita ("GDPpc") for region i, in country c, and year t; and $Uni_{ic,t}$ is the number of universities in the region[17] and Pop is the population. In the empirical application we lag the university coefficient by at least five years as there is unlikely to be immediate effect. Using the fifth lag seems natural as almost all students

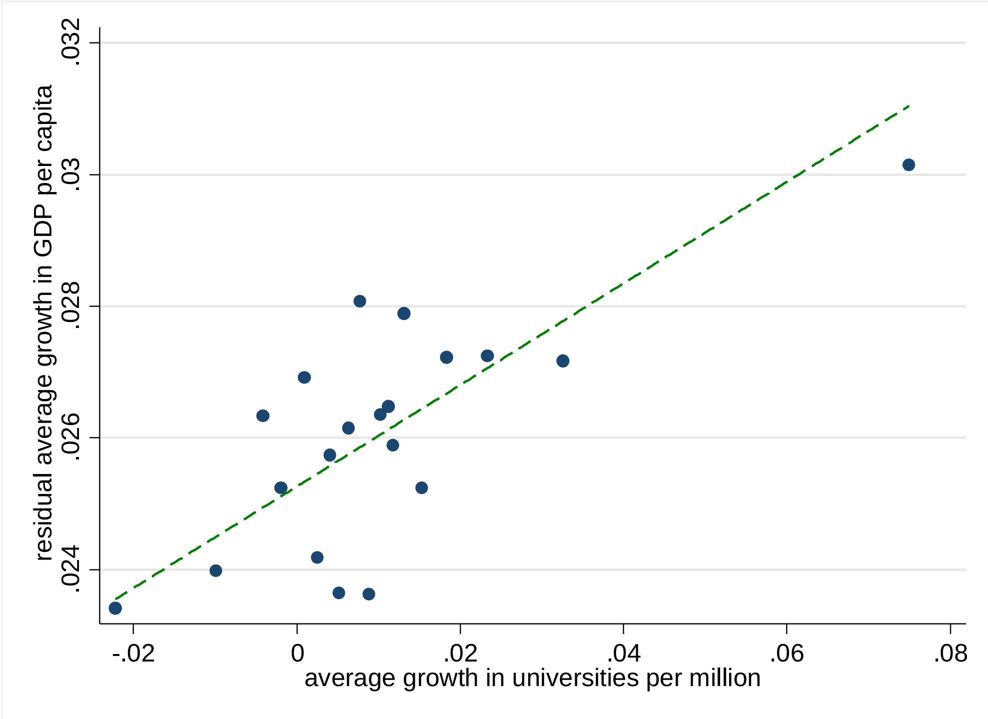
[15] It would be desirable to control for working age population, together with total population, since this is expected to affect production and growth. Unfortunately, demographic data at the regional level over time across a wide range of countries is not available, but we note that the region trends in our core regressions should control for demographic shifts.

[16] In addition, these graphs show that there are observations with very high university growth in the top bin. We explore which region-years were driving this found that they are evenly spread across 60 countries and different years, so they do not appear to be data errors. Dropping the observations in the highest growth bin actually strengthens the correlation in this simple scatter plot. We keep all the data in the main regressions, but show that the results are robust to dropping these observations or winsorising the top and bottom 5% observations of lagged university growth and GDP growth.

[17] We add 1 to the number of universities before taking logs so we can include region-years where there are no universities. We show robustness to other ways of dealing with the zeros such as dropping observations with no universities.

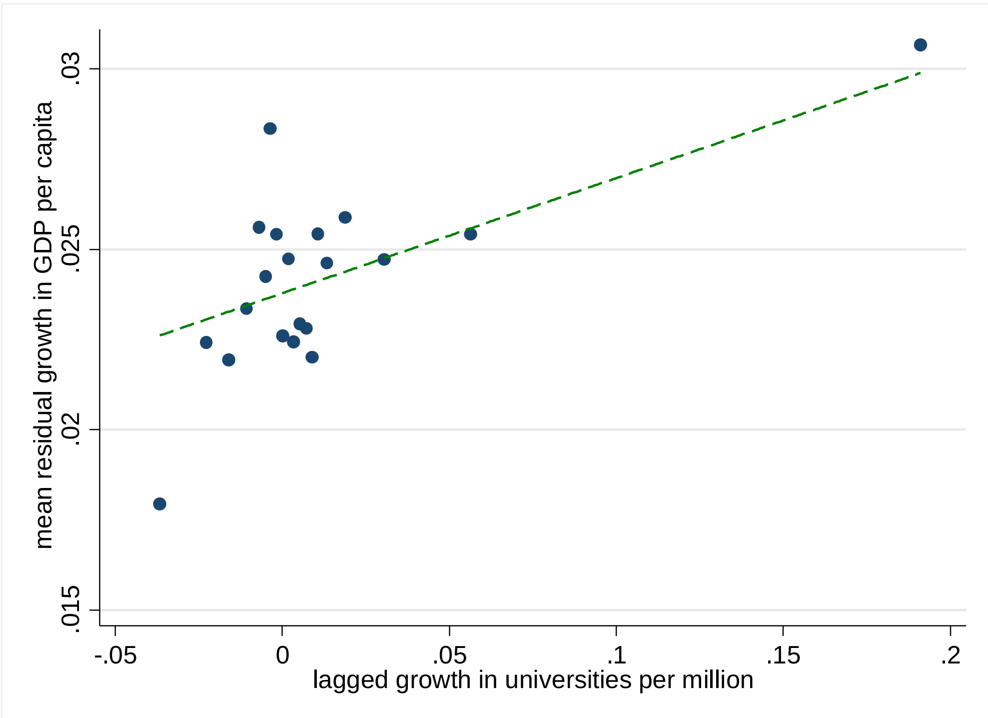
Figure 1.2.2: Regional GDP per Capita Growth and University Growth

A: Average growth rates, one observation per region



NOTES: 1,498 region observations are grouped equally into 20 bins, variation is within country. Source: WHED and Gennaioli et al. (2014) for regional GDP per capita and population

B: Average growth rates, region-year observations



NOTES: 8,128 region-year observations are grouped equally into 20 bins, variation is within country. Source: WHED and Gennaioli et al. (2014) for regional GDP per capita and population will have graduated in a five year period and it is standard practice to calculate growth rates in 5 year blocks (for example, Barro (2012), Gennaioli et al. (2014)). In addition, using the lag means that we eliminate the effects of a contemporaneous demand shock that raises GDP per capita and also results in the opening of new universities. Since the impact of universities could take place over a longer period of time we consider this to be a conservative approach.[18] We also look at results using longer distributed lags (which means losing more of the early years of the sample). These specifications result in larger long-run implied impacts of universities, presumably because it takes longer for human capital to build up in the area.

The cross sectional relationship is likely to be confounded by unobservable region-specific effects. To tackle this we estimate the model in long (five-year) differences to sweep out the fixed effects. Our main estimating model is therefore:

$$\Delta ln(Y/L_{ic,t}) = \alpha_1 \Delta ln(Uni_{ic,t-5}) + \alpha_2 \Delta ln(Pop_{ic,t-5}) + X'_{ic,t-5}\alpha_3 + \eta_i + \tau_t + \varepsilon_{ic,t} \qquad (1.3.2)$$

We control for a number of observables X , that may be related to GDP per capita growth and also the growth in universities including the lagged level of population, country and regional level GDP per capita (to allow for catch up) and $\varepsilon_{ic,t}$ an error term which we cluster at the region level. Finally, as well as time dummies (τ_t) we include region fixed effects (η_i) which in these difference equations allow for region-specific time trends, which is a demanding specification. We show the robustness of the results to including country by year dummies. We do not initially include any other measure of human capital and innovation in these specifications, so that we can capture the total effect that universities have on growth. However, we explore the effect of adding human capital and innovation when we try to pin down the mechanism through which universities impact on growth. Our data are from the match of the WHED and Gennaioli et al. (2014) databases which attempted to obtain university, education and GDP data from every sub-national region in the world. Since this is where the variation in the data lives we cluster standard errors at this regional level in our baseline results (see Abadie et al. (2017)). However, we also show more conservative approaches, for example clustering at

[18] For example, using cross country panel data, Dias and Tebaldi (2012) find effects of human capital growth on GDP growth with a 10 year lag; Breton and Breton (2016) show that increased average schooling takes around 40 years to translate into GDP increases; and Marconi (2018) shows that increases in secondary schooling only show up in GDP when workers are 45-64. Of course, the impact of universities does not necessarily only come from graduate supply. It may also come through university-business linkages, executive education and effects on institutions. We discuss these further below.

the country level.

We also explore the extent to which GDP per capita growth in region i may be affected by growth of universities in *other* regions within the same country and discuss this econometric specification in subsection 1.4.4 below.

1.4 Results

1.4.1 Basic Relationships

As an initial investigation, we examine the regional cross sectional correlations between universities and regional GDP per capita, based on the year 2000. Column (1) of Table 1.4.1 shows that there is a significant and positive correlation between GDP per capita and universities: controlling for population, a 10% increase in the number of universities is associated with around 6% higher GDP per capita. Column (2) includes country fixed effects which reduces the university coefficient substantially from 0.680 to 0.214. We include a host of further geographic controls in column (3) - whether the region contains a capital city, its latitude, inverse distance to ocean, malaria ecology and the log of cumulative oil and gas production.[19] This reduces the coefficient on universities still further to 0.160. In column (4) we add years of education. This reduces the coefficient on universities by around two-thirds.[20] In column (5) we repeat the column (2) specification but restrict to the sample for which patents data are available, and add years of education in column (6). Again, this reduces the coefficient on universities, by about half. In column (7), we see that adding a measure of patent "stock" reduces our coefficient on universities to 0.056, but it remains significant.

[19] Specifically, we take the natural log of 1+ this value, so that we retain zeroes in our sample.

[20] The coefficient on years of education is highly significant and similar in magnitude to the cross section results in Gennaioli et al. (2013). In regressions of regional income per capita on years of education, controlling for geographic characteristics, Gennaioli et al. (2013) estimate a coefficient of 0.2763, see their Table IV column (2).

Table 1.4.1: Cross-Sectional Regressions

Dependent variable: Regional GDP pc	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(1+#universities)	0.680***	0.214***	0.160***	0.0555***	0.164***	0.0744**	0.0557**
	(0.124)	(0.0422)	(0.0388)	(0.0206)	(0.0476)	(0.0313)	(0.0216)
ln(population)	-0.468***	-0.105**	-0.112***	-0.0692***	-0.100**	-0.0542*	-0.123***
	(0.0998)	(0.0412)	(0.0325)	(0.0233)	(0.0410)	(0.0274)	(0.0323)
Years of Education				0.292***		0.283***	0.237***
				(0.0280)		(0.0338)	(0.0398)
ln(1+EPO Patent "stock")							0.0812***
							(0.0182)
Observations	1213	1213	1182	1182	619	619	619
# clusters	65	65	62	62	34	34	34
country dummies	no	yes	yes	yes	yes	yes	yes
region controls	no	no	yes	yes	yes	yes	yes

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. OLS estimates based on data in 2000. Standard errors clustered at the country level. Column (1) shows the relationship between universities and the natural log of GDP per capita, controlling for population. Column (2) includes country dummies. Column (3) includes regional controls (a dummy indicating whether the region contains a capital city, together with latitude, inverse distance to ocean, malaria ecology, log(oil and gas production) 1950-2010, these are not reported here). Column (4) includes years of education. Column (5) is the same specification as column (3) but restricts the sample to the regions for which OECD REGPAT patents are available. Column (6) includes years of education, and column (7) includes the natural log of the regional patent "stock". We add one to the number of universities and to patents before taking logs.

1.4.2 Main Results

Table 1.4.2 presents our main results on our core sample.[21] Column (1) is a simple correlation between the growth of regional GDP per capita and the lagged growth of universities with no other controls. The estimated coefficient is 0.0469 and highly significant.

To control for the fact that populous regions are more likely to require more universities, we add the lagged level of the population in column (2) which lowers the university coefficient slightly. Adding country and year fixed effects in column (3) has little effect. In column (4) we add the lagged level of regional GDP per capita (as in the convergence literature from Barro (2012) – see below), the growth in population, and several regional covariates (latitude, inverse distance to the coast, malaria ecology, and oil and gas production since 1950) and a dummy for the region with the capital city. In column (5) we control for lagged country-level GDP per capita which should capture time varying macro shocks. Columns (6) and (7) replicate columns (4) and (5) but include *regional fixed effects*, a very demanding specification which allows for regional trends. These do not much affect the university coefficient and in fact it is higher at 0.0467 in the most general specification. Overall, these results suggest that on average, a 10% increase in the number of universities in a region is associated with around 0.4% higher GDP per person.[22] Our baseline results cluster at the regional level, but column (8) clusters the standard errors at the much more conservative level of the country and shows that the coefficient on universities remains significant. Finally column (9) includes a full set of country by year dummies which is a very demanding specification. Although the coefficient on universities falls by about half, it remains significant.

[21] Allowing for the lag structure, the panel covers 11 waves, from 1960 to 2010 and spans 1498 regions. The panel is unbalanced, driven by the availability of regional economic data which is better in later years. For example, in the core sample of 8,128 region years, there are only 211 observations of GDP per capita growth in 1960 (which requires regional GDP per capita in 1955 for its calculation). This sample includes advanced economies like UK, US, Germany, France and Italy, and some South American countries like Brazil and Mexico. By contrast, most regions are included in our sample in the later years (for example 1304 of the 1498 regions are observed in 2005) though economic data are not available for some countries in later years (for example data for Venezuela spans 1960-1990).

[22] Our analysis is carried out on a sample that drops 54 observations from China pre 1970, before and during the Cultural Revolution, when universities were shut down. Our effects survive if these observations are included, with the coefficient on university growth becoming 0.0320, still significant at the 1% level. We drop them because of the unique nature of this historical episode and the fact that this small number of observations (less than 1% of the full sample) seem to have a large effect on the coefficient.

Table 1.4.2: Baseline Results

Dependent variable: Regional growth in GDP per capita	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged growth in #universities	0.0469***	0.0363***	0.0400***	0.0456***	0.0444***	0.0447***	0.0467***	0.0467***	0.0226**
	(0.0104)	(0.0105)	(0.0112)	(0.0106)	(0.0105)	(0.0107)	(0.0107)	(0.0162)	(0.00992)
Lagged level of regional GDP per capita				-0.0153***	-0.0127***	-0.0581***	-0.0776***	-0.0776***	-0.0774***
				(0.00125)	(0.00131)	(0.00325)	(0.00478)	(0.00688)	(0.00460)
Lagged level of country GDP per capita					-0.0213***		0.0378***	0.0378**	
					(0.00422)		(0.00611)	(0.0179)	
Lagged level of population /100		0.178***	-0.0301	-0.0765*	-0.0855**	-1.095***	-0.850**	-0.850	-1.724***
		(0.0324)	(0.0351)	(0.0395)	(0.0387)	(0.333)	(0.352)	(0.720)	(0.476)
Lagged growth in population				-0.0986**	-0.113***	-0.209***	-0.183***	-0.183***	-0.182***
				(0.0383)	(0.0385)	(0.0446)	(0.0452)	(0.0676)	(0.0502)
Dummy for capital in region				0.0125***	0.0110***				
				(0.00170)	(0.00168)				
Observations	8128	8128	8128	8128	8128	8128	8128	8128	8128
# clusters	1498	1498	1498	1498	1498	1498	1498	78	1498
clustering	Region	Region	Region	Region	Region	Region	Region	Country	Region
year dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
country dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
region controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
region trends	No	No	No	No	No	Yes	Yes	Yes	Yes
country by year dummies	No	No	No	No	No	No	No	No	Yes

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. OLS estimates, 78 countries. Column (1) is a simple correlation between regional GDP per capita growth and the lagged growth in university numbers. Column (2) controls for the lagged log of population. Column (3) includes country and year dummies. Column (4) controls for lagged regional GDP per capita, the lagged growth in population, the lagged log population level, a dummy for whether the region contains a capital city, together with latitude, inverse distance to ocean, malaria ecology, log(oil and gas production) 1950-2010 (not reported here). Column (5) adds lagged country GDP per capita. Column (6) includes regional fixed effects, and the time varying controls of column (4). Column (7) adds lagged country GDP per capita. Standard errors are clustered at the regional level except in column (8) where they are clustered at the country level. Levels of GDP per capita and population are in natural logs.

The other variables in the regressions take the expected signs. The coefficient on the regional convergence term is nearly 2% in columns (4) and (5).[23] Country GDP per capita has a negative coefficient in these specifications. This becomes a positive relationship once regional fixed effects are included. Having a capital city in a region is associated with around one percentage point higher regional GDP per capita growth. In the Appendix, we show that the geographic controls in columns (4) and (5) generally have the expected signs.

We explore different distributed lag structures, and find that in general a single five year lag is a reasonable summary of the data, although there are smaller but significant effects at the 10 year lag, and even the 25 year lag on the full sample[24] (see Appendix). We might expect the effect of universities on regional GDP to grow over time, due to the gradual accumulation of graduates entering the workforce, or the building of regional innovative capacity. However, over longer time frames, there are more factors at play which are not captured in our estimation framework, and our sample is reduced since a longer time series of economic data is not available for all countries. Interestingly, the contemporaneous (unlagged) effect of university growth is zero or negative (although not significant), suggesting that it takes some time for benefits to be felt, while presumably some costs are incurred at the regional level. There is some evidence for stronger effects at the 10 year lag and longer lags when considering only the US, UK, France and West Germany (advanced Western economies which we might associate with the "Sputnik Crisis").

1.4.3 Robustness and Heterogeneity

Specification and Sample Checks

We conduct a large number of robustness checks on our baseline specifications with and without regional trends (i.e. columns (5) and (7) of Table 1.4.2), as detailed in the Appendix. Firstly, we do a block of *specification* checks: weighting by the region's population share; controlling for the current population changes (to partially address the concern that the effect of the university is simply to pull in more people to the region, who spend or produce more and hence raise GDP per capita growth – see section 1.5 below); and using growth in university density instead of the count. Secondly, we check *sampling*

[23] In the fixed effects specifications (7) and (8) this is larger, potentially reflecting the downward (Nickell-Hurwicz) bias in the coefficient of the lagged dependent variable which is particularly an issue in short panels (see Barro (2012) and Gennaioli et al. (2014)).

[24] A similar pattern is found when we include each lag separately.

issues: dropping regions which never have a university; dropping region-years with no universities; dropping the observation when a region opens its first university; winsorising the top and bottom 5% of university growth and/or GDP per capita growth as the dependent variable and dropping observations where we have interpolated GDP per capita. A third set of *measurement* issues includes adding a dummy for regions where more than 5% of universities in the original listing have missing founding dates (and are therefore excluded from our analysis) and exploring whether the definition of university in WHED (i.e. only institutions that offer four year courses or postgraduate degrees) may be a problem. The results are robust to all these checks (and some others described in the Appendix).

Finally, to investigate the potential concern that our results are driven by expectations of growth in the region we explore "Granger Causality" tests. We use the growth in universities as the dependent variable and regress this on the lagged growth in regional GDP per capita, and the other controls. We see that even as all controls are added, the lagged growth of regional GDP per capita has no relationship with current growth in universities and does not appear to "Granger cause" the opening up of universities.[25] As another test of reverse causality, we add lagged growth in regional GDP per capita to our core specification and find that the coefficient on universities rises to 0.0525 and remains significant.[26]

Heterogeneity

To examine the heterogeneity in the university coefficient we first examine whether the university effect differs by groups of countries where we have reasonable numbers of observations: (i) the US, UK, France and West Germany; (ii) the rest of Europe and Canada; (iv) Latin America; (v) Asia (including Australia) and (vi) Africa. There is a positive relationship between university growth and growth in regional GDP per capita in all areas ranging from coefficients of 0.004 to 0.116 (see Appendix), although it is not significant in some groupings. We also examined whether there is heterogeneity across time periods within these groupings. It is interesting to note that in US, France, West Germany and the UK there are significant effects in the pre-1990 period and post-1990 period. Conversely, in

[25] Interestingly, there is a negative and significant relationship between university growth and the lagged level of universities, suggesting catch-up. Similarly there is a negative relationship between lagged years of education and university growth. There is however, a positive relationship between the growth in years of education and university growth.

[26] While empirical evidence suggests that current growth is not a good predictor of future growth in the long-run (Easterly et al., 1993), there might be persistence in the short run. If this is the case, and lagged growth in universities is correlated with lagged growth in regional GDP per capita, then our results could be affected by reverse causality.

Asian countries, we find that there is a positive significant coefficient on university growth in the post 1990 period only.

We also test whether within a country, the university effect is driven by richer or poorer regions – the latter being consistent with catch-up growth. We find that interacting the university effect with a variable that normalises a region's GDP per capita by that country's frontier region (the region with the highest GDP per capita in that year) gives a negative and significant coefficient. It does appear therefore that new universities have a stronger impact on laggard regions within a country.

University size and quality

A concern with our econometric strategy is that our use of university numbers is a very imperfect measure of university presence. Universities are not homogeneous, but vary in size and quality. Clearly, both of these dimensions are likely to matter in terms of economic impact (although it is not obvious why this would necessarily generate any *upwards* bias in our estimates). An alternative measure would be to use changes in enrolments over time. Even if such data were available for all countries (which it is not) one would be particularly concerned about demand side endogeneity driving enrolments. This issue notwithstanding, we can focus on the United States where state level enrolments dating from 1970 are published by the National Center for Education Statistics (NCES).[27] We find that university numbers and total enrolments are highly correlated (around 0.9 in a given year) and that there is a strong positive relationship between the growth in universities and growth in students between 1970-2010.[28] This gives us some reassurance that the number of universities is a reasonable measure of university presence at the regional/state level.

Ideally, to measure quality we would like to have global rankings for all our institutions, carried out annually throughout our sample period.[29] However, university rankings tables only tend to cover the top few hundred institutions in the world, and tend to be available only for recent years.[30] Our data do contain some key attributes of universities which may be indicative of quality, specifically whether or not a university is a research institution (as

[27] See http://nces.ed.gov/fastfacts/display.asp?id=98.

[28] See Figure 1.C.4 in the Appendix.

[29] Some studies have considered the quality dimension within individual countries. For example, using data from the UK, Abramovsky and Simpson (2011) find that research quality affects the location of firm R&D; and Helmers and Rogers (2015) find that university quality affects the patenting of small firms. Valero (2018) also finds that universities of higher quality in the UK have a larger impact on start-up activity and productivity in nearby firms.

[30] For example, the Shanghai Rankings have been compiled since 2003 and cover the world's top 500 universities.

Table 1.4.3: Differences in University Quality

Dependent variable: Regional Growth in GDP pc	(1)	(2)	(3)	(4)	(5)
A: Full sample					
Lagged growth in #unis	0.0467***	0.0512***	0.0415***	0.0496***	0.0462***
	(0.0107)	(0.0123)	(0.0127)	(0.0129)	(0.0137)
Lagged growth in PhD share		-0.00272			-0.00447
		(0.00289)			(0.00392)
Lagged growth in STEM share			0.00203		0.00520
			(0.00303)		(0.00332)
Lagged growth in prof. share				-0.000988	-0.00187
				(0.00309)	(0.00351)
Observations	8128	8128	8128	8128	8128
B: US, UK, FR, DE					
Lagged growth in #unis	0.0509***	0.0166	0.0182	0.0311*	0.0136
	(0.0157)	(0.0157)	(0.0176)	(0.0174)	(0.0172)
Lagged growth in PhD share		0.0171***			0.0146**
		(0.00421)			(0.00634)
Lagged growth in STEM share			0.0153***		0.00383
			(0.00398)		(0.00429)
Lagged growth in prof. share				0.00988**	-0.0000893
				(0.00482)	(0.00722)
Observations	1023	1023	1023	1023	1023
C: All other countries					
Lagged growth in #unis	0.0482***	0.0539***	0.0437***	0.0519***	0.0487***
	(0.0112)	(0.0129)	(0.0135)	(0.0137)	(0.0145)
Lagged growth in PhD share		-0.00352			-0.00524
		(0.00307)			(0.00409)
Lagged growth in STEM share			0.00176		0.00518
			(0.00318)		(0.00345)
Lagged growth in prof. share				-0.00125	-0.00182
				(0.00325)	(0.00370)
Observations	7105	7105	7105	7105	7105

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Panel A includes the full sample of countries, and Panel B restricts to the US, UK, France and West Germany. Within each panel, our core regression (Column (7) from Table 1.4.2) is replicated in column (1). Then in columns (2) to (5), the lagged growth of the shares of universities of different types are added as labelled.

indicated by whether or not a university can grant PhDs); whether it offers STEM (science, technology, engineering or mathematics) subjects, and whether it offers "professional service" related courses (which we define as business, economics, law, accounting or finance related courses).[31] Table 1.4.3 adds these variables to the analysis by considering

[31] The way we ascertain subjects offered by each university is by extracting key relevant words from the information provided in WHED. For some universities the descriptions offered can be quite broad (e.g. it may specify "social sciences" instead of listing out individual subjects). We try to keep our STEM and professional course categories broad to account for this, but there are likely to be cases where we do not pick up the accurate subject mix at a university.

the effect of the growth in the share of each type of university over and above the growth in the number of all universities.[32] Panel A shows the result for the full sample of countries. Each column includes one of these measures in turn. The effects are not significantly different from zero, suggesting that on the entire sample there seems to be a general university effect which does not vary much by type of university as defined here.

Again, we disaggregate this analysis between the more advanced economies of Western Europe and the US in Panel B of Table 1.4.3 and other countries (in Panel C). Increases in the share of PhD granting institutions, STEM and professional course institutions *are* significant in Panel B but not in Panel C. When all of these shares are included together in column (5), only the share of PhD granting institutions remains significant. This analysis is suggestive evidence that the research channel may be more important in countries nearer the technology "frontier" (as in Aghion, Meghir and Vandenbussche (2006)).

Barro growth regressions

Our main specifications in Table 1.4.2 included lagged regional (and country) GDP per capita, as is standard in growth regressions to capture convergence. There are of course issues of bias when including a lagged dependent variable, particularly in fixed effects regressions with a short time dimension,[33] and in fact our baseline results are robust to dropping these regressors.[34] An alternative econometric approach is to consider "conditional convergence" regressions (Barro, 1991, 2012). In the Appendix (Table 1.D.7) we replicate as closely as possible the results in Gennaioli et al. (2014). Column (1) has their basic specification and column (2) includes years of education. Columns (3) and (4) repeat these specifications but adds in the lagged level of universities.[35] Universities have a positive and significant coefficient over and above years of education. As we would expect if some of the effect of universities is via their production of human capital, the effect of universities is higher when years of education are omitted. Note that the interpretation of the university coefficient is different because in steady state we need to divide by the absolute value of the convergence coefficient (0.015). This implies a 10% increase in universities generates a 1.6% increase in long-run GDP per capita (=

[32] We note that these characteristics apply to the universities' status in 2010. In the absence of a full time series of when universities begin to offer different courses or qualifications, we simply assume that these characteristics apply since the universities were founded.

[33] See Hurwicz (1950) and Nickell (1981), and discussion in the context of growth regressions in Barro (2012).

[34] Estimating our core regression (Table 1.4.2, column (7) without lagged regional and country GDP per capita, the coefficient is 0.0434, significant at the 1% level.

[35] Column (1) follows their Table 5, column (8), omitting years of education, and column (2) includes years of education. The coefficients are very similar: the convergence term is between 1.4% and 1.8%, and the coefficient on years of education is nearly identical at around 0.004.

$0.1 * 0.00243/0.015$). This is much *larger* than our baseline estimates of 0.4%. Due to the econometric difficulties of interpreting the coefficient on the lagged dependent variable in these kind of dynamic panel data models, we prefer our baseline estimates, but note that we might be under-estimating the strength of the growth- university relationship in our more conservative approach.[36] Finally, to understand better the difference between the growth and levels effects, we include also the lagged level of universities in our core regression (Table 1.4.2, column (7)). This actually raises the coefficient on lagged university growth to 0.0587, still significant at the 1% level. The coefficient on the lagged level of universities is -0.00452 (significant at the 5% level), so it does not appear that there is any substantive effect of the level of universities on growth.

Summary on robustness

We have shown that our results are robust to different specification and, to the extent that the data allow, consideration of the size and quality dimensions. However, this framework does not allow us to address potential endogeneity due to time-varying unobservables. Although there is no direct way to address this without an external instrumental variable, there are non-trivial time lags between (i) an unobservable local shock and a policy decision to build a university; (ii) the decision to build and opening up of the institution and (iii) the opening of the university and the economic impact. Hence, in our view such local shocks are unlikely to be the reason we observe the relationships documented in our data.

1.4.4 Geographical Spillover Effects of Universities

If the effects we are finding are real we would expect to see that universities do not just affect the region in which they are located, but also neighbouring regions. To examine this we extend equation 1.3.2 to include the growth of universities in other regions, which may be the nearest region (*j*) or simply all other regions in the country (-*i*). Therefore, we include the growth in region *i*'s own universities ($\Delta ln(Uni_{ic,t-5})$) as well as a potential

[36] Table 1.D.8 in the Appendix presents a similar analysis, but in long difference format. For each region the dependent variable is the average annual growth rate over a 50, 40 or 30 year time horizon to 2010. This is regressed on starting period universities and other controls. The samples differ according to availability of regional economic data over different time frames. These specifications also show positive (and significant in the case of the 50 year and 30 year differences) relationships between initial period universities and subsequent growth once country fixed effects are included.

spillover effect from universities located in neighbouring regions ($\Delta ln(Uni_{jc,t-5})$):

$$\begin{aligned}\Delta ln(Y/L_{ic,t}) = \theta_1 \Delta ln(Uni_{ic,t-5}) + \theta_2 \Delta ln(Uni_{jc,t-5}) + X'_{ic,t-5}\theta_3 + X'_{jc,t-5}\theta_4 \\ +\eta_i + \tau_t + u_{ic,t}\end{aligned} \tag{1.4.1}$$

The lagged population level and population growth in region j are in the controls, ($X'_{jc,t-5}$).

We allow for spatial variation by interacting university growth with the term $dist_j$ which is the distance between region i and its nearest region j relative to the median distance to nearest region in the same country, see equation 1.4.2. This measure is time invariant, so the term itself in absorbed by region fixed effects. The estimating equation therefore becomes:

$$\begin{aligned}\Delta ln(Y/L_{ic,t}) = \phi_1 \Delta ln(Uni_{ic,t-5}) + \phi_2 \Delta ln(Uni_{jc,t-5}) + \phi_3 dist_j * \Delta ln(Uni_{jc,t-5}) \\ +X'_{ic,t-5}\phi_4 + X'_{jc,t-5}\phi_5 + \eta_i + \tau_t + u_{ic,t}\end{aligned} \tag{1.4.2}$$

where the effect of the nearest region of median distance within a country (so the distance term equals 1) is $\phi_2 + \phi_3$. We expect ϕ_3 to be negative so that the effect of region j gets smaller for regions further away within a country.

Table 1.4.4 contains the spillover analysis with column (1) replicating our baseline result with column (2) including lagged university growth in the nearest region. This shows that universities in the nearest region have a positive but insignificant association with home region growth. However, on closer inspection it appears that some "nearest regions" are actually very geographically distant. A fifth of observations are in regions over 200km from the next nearest region (based on distance between centroids), so column (3) we drop these observations. In this sample the nearest region university coefficient is around half the magnitude of the home region's universities. Therefore, using the full sample again in column (4), we control for the growth in universities in the nearest region interacted with the distance to that region relative to the country's median.[37] Consistent with column (3), the interaction is negative and significant. In column (5) we add the relevant controls for the neighbouring region – the lagged population and population growth (which should also control for a demand shock in the neighbouring region in the previous period). These have little effect on our coefficients or their significance.

[37] We take this measure relative to median to reduce the effects of outliers (for example Hawaii and Alaska in the US). However, the results are similar when we normalise by country mean.

Table 1.4.4: University Spillovers from Other Regions

Dependent variable: Regional Growth in GDP per capita	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged growth in #universities	0.0467***	0.0444***	0.0443***	0.0439***	0.0437***	0.0348***	0.0368***
	(0.0107)	(0.0106)	(0.0118)	(0.0106)	(0.0105)	(0.0107)	(0.0107)
Lagged growth in #universities, nearest region		0.0122	0.0221**	0.0490***	0.0494***		
		(0.0105)	(0.0110)	(0.0170)	(0.0172)		
Lagged growth in #universities X "dist"				-0.0326***	-0.0332***		
				(0.0120)	(0.0121)		
Lagged growth in #universities in other regions						0.0588***	0.0612***
						(0.0132)	(0.0133)
Observations	8128	8128	6544	8128	8128	8128	8128
# clusters	1498	1498	1257	1498	1498	1498	1498
Nearest / other region controls	No	No	No	No	Yes	No	Yes

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Column (1) replicates our core regression (column (7) from Table 1.4.2). Column (2) adds in the lagged growth in universities in the nearest region. Column (3) replicates column (2) but conditions the sample to regions whose nearest region is less than 200km away. Column (4) returns to the full sample, but adds an interaction term of universities with the ratio of the distance to nearest region to the median distance to nearest region in the country ("dist"). Column (5) adds controls from the nearby region: namely the lagged population and population growth (not reported here). There were a small number of observations where the population in the nearest region was missing, relating to early years in the sample period. In this case, population was extrapolated back in time, using a log-linear trend, and a dummy variable included to indicate this. Column (6) includes the lagged growth in universities in all other regions of the country, and column (7) also adds the relevant controls from all other regions in the country: namely the lagged population and population growth (again with a dummy to indicate where the population in the rest of the country has been calculated with missing values for any regions that year).

Finally, we look at the effects of university growth in all other regions (including nearest region) in the country on our home region. Column (6) adds the lagged growth in universities in all regions of a country, excluding the home region. Column (7) also adds the relevant controls (lagged population and population growth for the other regions). These effects are now larger than our main effect and again highly significant.[38] The implication is that a 10% increase in universities in the rest of the country (which in most cases will represent a greater absolute increase than a 10% increase in home region universities) is associated with an increase in home region's GDP per capita of around 0.6 per cent.

Overall, this analysis suggests that universities not only affect the region in which they are built, but also their neighbours and that there does appear to be a spatial dimension to this, in the sense that geographically closer regions have stronger effects.

1.4.5 Magnitudes

Using the coefficients in Table 1.4.4 we can estimate a country-wide effect of a university expansion on the typical region in our dataset. The average region has nearly 10 universities (see Table 1.2.1), and the average country has 20 regions (and therefore 200 universities). Increasing the universities in one region by 10% (from 10 to 11) is associated with a 0.4% uplift to its GDP per capita according to our main result. For each other region, this represents a 0.5% increase in universities in the rest of the country (a rise from 190 universities to 191). Multiplied by 6% (the coefficient on other regions in column (7) of Table 1.4.4), this implies an uplift to all other regions' GDP per capita of 0.03%. Assuming the regions in this hypothetical country are identical, the uplift to country-wide GDP per capita is simply the average of these effects: 0.05%.

As a sense check for this result, we collapse our regional dataset to the country level and run macro regressions of GDP per capita growth on lagged university growth. The coefficient on universities is 0.047 (but insignificant). According to these results, a 10% increase in universities at the country level would be associated with a 0.47% increase in GDP per capita. Therefore a 0.5% increase in universities at the country level (equivalent to our hypothetical expansion) would imply a 0.03% uplift – this is smaller (but in the same ballpark) as the 0.05% we calculate using the results from our better identified regional

[38] Standard errors in this analysis are clustered at the region level. Conservatively clustering at the country level does not affect significance in the nearest region analysis. The coefficients on growth in all other regions (columns (6) and (7)) remain significant at the 10% level.

analysis.

While this seems like a significant amount of benefit, we also need to consider the costs of university expansion.[39] Given that the costs of building and maintaining universities will vary widely by country, we choose to focus on a particular institutional setting for this calculation. In the UK in 2010, there were 171 universities across its 10 regions. As an experiment we add one university to each region, a total increase of 10 universities (6%) at the country level. Using similar steps as in our hypothetical country above (but taking into account the actual numbers of universities in each UK region in 2010), we calculate that the overall increase to GDP per capita (or GDP, assuming population is held constant) is around 0.7%.[40] Applied to UK GDP in 2010 (£1,614 billion according to the ONS[41]) this comes to just over £11 billion per year. A crude approximation of the annual costs associated with a university can be made based on university finance data: in 2009-2010 the average expenditure per institution in the UK was around £160 million.[42] Multiplying this by the 10 universities in our experiment, the implied annual cost for the additional universities is £1.6bn, or 0.1% of GDP. So, in this example the potential benefits of university expansion appear far larger than the costs (0.7% vs. 0.1%).

While this calculation is highly simplified, it shows that there is a large margin between the potential benefits of university expansion implied by our regression results and likely costs. We note that the costs of setting up universities, and methods of university finance vary by country so we cannot generalise this result to other countries, nor make statements about the optimal number of universities in particular regions. Similar calculations for

[39] It is unlikely that these are controlled for in our regressions: a large portion of university financing tends to be at the national level, and costs are incurred on an ongoing basis (e.g. property rental or amortisation and staff salaries are incurred every year) and so would not be fully captured by the inclusion of lagged country GDP per capita as a covariate.

[40] For each of the ten regions in the UK in turn, we calculate the log difference implied by adding one university to that region's universities, and multiply this by 0.04 (of the coefficient on university growth from Table 1.4.2 column (7)). We then calculate the log difference in the count of universities in all other regions, and raise home region GDP per capita by that multiplied by 0.06 (of the coefficient on university growth in "other regions" from Table 1.4.4). We abstract from the 5 year lag in this calculation. We then add up the total uplifted GDP across regions, and divide by total population (assumed unchanged).

[41] Series ABMI, Gross Domestic Product: chained volume measures: Seasonally adjusted £m, Base period 2012

[42] Data on university finance, by institution, can be found at the UK Higher Education Statistical Authority (HESA) website (https://www.hesa.ac.uk/index.php?option=com_content& view=article& id=1900& Itemid=634). Total expenditure in the year 2009/10 was nearly £26 billion across 163 institutions listed in HESA, implying around £160 million per institution. University expenditure contains staff costs, other operating expenses, depreciation, interest and other finance costs. We checked if this figure has been relatively stable over time, finding that by 2013-14, average expenditure was £180 million. At this higher amount, the implied costs of our expansion rise to 0.11% of GDP. Note that the number of institutions present in 2010 was 171. The majority of institutions in WHED correspond to those listed in HESA, but there are a small number of discrepancies due to differences in the classifications of some institutes or colleges between the two listings. This does not matter for our purposes, as are simply using the HESA data to calculate the average expenditure of a typical university.

other countries could be made by delving into particular institutional settings.

1.5 Mechanisms

Having established a robust association of GDP per capita with universities we now turn to trying to understand the mechanisms through which universities may affect growth.

1.5.1 Human Capital

We add measures of growth in human capital to our baseline regressions to see how this influences the university coefficient. In Table 1.5.1 we consider the relationship between universities and college share. Column (1) replicates the core result from Table 1.4.2 column (7), and column (2) shows the same specification on the reduced sample where college share is non-missing, for which the university coefficient is a bit larger at 0.08. Column (3) adds the lagged growth in college share which in itself is highly significant, and reduces the university coefficient slightly from 0.0843 to 0.0802. Column (4) uses contemporaneous growth in college share and column (5) adds in the lagged college share which reduces the coefficient to 0.0775. This represents a reduction in the university coefficient of 8% compared with column (2).

In column (6) we include also the level with both lags, with little change in the university coefficient. In column (7) we look at the raw correlation between contemporaneous growth and the lagged growth in universities (with only country fixed effects as controls), and find it to be relatively small but highly significant. Adding all the other controls dampens this relationship further and this small effect of university growth on college share is what explains the fact that adding in growth in human capital causes only a small reduction in the coefficient on universities. This analysis suggests that a 1% rise in the number of universities gives rise to around a 0.4 percentage point rise in the college share.[43]

[43] Table 1.D.9 in the Appendix uses another measure of human capital: years of education, which is available for a larger sample of countries and years. The qualitative results are similar. The Appendix 1.B.2 also gives some simple simulations showing that the magnitude of effect of universities on human capital is consistent with the variation we are using in the data.

Table 1.5.1: Universities and Share of Educated Workers

Dependent Variable:	(1) Δ GDPpc	(2) Δ GDPpc	(3) Δ GDPpc	(4) Δ GDPpc	(5) Δ GDPpc	(6) Δ GDPpc	(7) Δ % college	(8) Δ % college
Lagged growth in #universities	0.0467***	0.0843***	0.0802***	0.0808***	0.0775***	0.0775***	0.00514***	0.00411***
	(0.0107)	(0.0135)	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.00139)	(0.00114)
Lagged growth in college share			2.237***		2.077***	2.075***		
			(0.362)		(0.323)	(0.326)		
Current growth in college share				0.847***	0.721***	0.722***		
				(0.148)	(0.130)	(0.132)		
Lagged level of college share						0.000727		
						(0.0225)		
Lagged level of regional GDP p.c.	-0.0776***	-0.0929***	-0.0942***	-0.0933***	-0.0944***	-0.0944***		0.000396
	(0.00478)	(0.00665)	(0.00659)	(0.00665)	(0.00660)	(0.00661)		(0.000287)
Lagged level of country GDP p.c.	0.0378***	0.0252***	0.0274***	0.0263***	0.0282***	0.0282***		-0.00139***
	(0.00611)	(0.00773)	(0.00761)	(0.00771)	(0.00760)	(0.00766)		(0.000433)
Lagged level of population/100	-0.850**	-2.136***	-2.226***	-2.289***	-2.350***	-2.348***		0.181***
	(0.352)	(0.452)	(0.451)	(0.456)	(0.456)	(0.457)		(0.0383)
Lagged growth in population	-0.183***	-0.0641	-0.0648	-0.0659	-0.0663	-0.0664		0.00218
	(0.0452)	(0.0523)	(0.0545)	(0.0533)	(0.0552)	(0.0552)		(0.00342)
Observations	8128	5118	5118	5118	5118	5118	5118	5118
# clusters	1498	1089	1089	1089	1089	1089	1089	1089

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Growth in college share is simply the percentage point difference: (college share (t) – college share (t-5))/5. Column (1) replicates Column (7) from Table 1.4.2. Column (2) restricts to the sample for which the change in college share is available. Column (3) drops the lagged growth in college share. Column (4) adds the contemporaneous change in college share. Column (5) includes both lagged and contemporaneous changes. Column (6) further adds the lagged level of college share (unlogged). Column (7) regresses the change in college share on the lagged growth in universities, with country dummies, but no other controls. Column (8) adds all the other controls.

1.5.2 Innovation

The best measure of innovation output available consistently at the regional level over time is patents, although unfortunately patents with locational information are not available for our entire sample of countries and years. We consider the effects of adding the growth in cumulative patent stocks[44] to our regressions, using patents filed at the European Patent Office which are available for over 38 of our countries between 1975 and 2010 (Table 1.5.2). Column (1) runs the core regression for the this sample of countries, and over the time period that we have patents data. Column (2) then includes the contemporaneous change in patents stock (allowing five years for the university growth to have an effect), which reduces the coefficient on university growth from 0.0156 to 0.0126 (a reduction of nearly 20 per cent). Patents themselves have a positive and significant association with GDP per capita growth: A 10% increase in the patent stock is associated with 0.5% higher per capita GDP. Column (3) considers the raw correlation between lagged university growth and current patent stock growth (including only year dummies), and shows it is positive but not significant. Column (4) then adds the standard controls with little effect.

This analysis provides tentative evidence that innovation is part of the story of why universities have an economic impact, though not the entire story. This may be because the effect of newer universities on patents takes a while to accumulate.

1.5.3 Institutions and Democracy

The use of country fixed effects throughout our analysis should rule out the possibility that the effects of universities simply reflect different (time invariant) institutions, since these tend to differ mainly at the country level. We have shown that the results survive the inclusion of country-year fixed effects in the robustness, this would capture country specific changes in institutions or changes in government. To the extent that time invariant institutions vary within countries, say at the US state level, our regional fixed effects analysis should address this.

Institutions do vary over time, however, and it is possible that universities contribute to this. There is a positive and significant correlation between country level democratic institutions (as proxied by Polity scores[45]) and universities. This correlation also exists when

[44] Patent stocks are calculated with an assumed depreciation rate of 15%. Initial patent stocks are calculated by dividing the first observed patent flow for a region by the depreciation rate plus the average growth rate in patents flow over the sample period for that region. Results are not sensitive to alternative depreciation assumptions.

[45] Polity scores were sourced from the Policy IV project (http://www.systemicpeace.org/inscrdata.html),

Table 1.5.2: Universities and Innovation

Dependent Variable:	(1) Δ GDPpc	(2) Δ GDPpc	(3) Δ patents	(4) Δ patents
Lagged growth in #universities	0.0156	0.0126	0.0300	0.0310
	(0.0143)	(0.0137)	(0.0547)	(0.0552)
Growth in EPO patent "stock"		0.0540***		
		(0.00581)		
Lagged level of regional GDP per capita	-0.0956***	-0.0963***		
	(0.00706)	(0.00679)		
Lagged level of country GDP per capita	0.0729***	0.0688***		
	(0.00815)	(0.00773)		
Lagged level of population/100	2.604***	2.151***		7.709***
	(0.766)	(0.740)		(2.271)
Lagged growth in population	-0.201***	-0.177***		-0.499***
	(0.0612)	(0.0587)		(0.158)
Observations	3559	3559	3559	3559
# clusters	757	757	757	757

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Column (1) replicates our core regression (column (7) from Table 1.4.2), but restricts to the relevant sample for patents data. Column (2) adds in the contemporaneous growth in cumulative patent "stock" to the regression. Column (3) regresses the growth in patent stock on the growth in universities as a raw correlation, with no other controls. Column (4) then adds the standard time varying controls (reported) and geographic controls (not reported).

we consider the 1960-2000 change in universities and polity scores (see the Appendix for more discussion). To our knowledge, a time series of data on regional institutions over our sample period is not available, but we can explore the relationships between perceptions of democracy, as obtained from the "World Values Survey" and lagged university presence in the cross section. Our measure is a categorical variable which gives the approval of a democratic system for governing one's own country, as this is more widely available across survey waves compared with other questions on democracy.[46] We note however, that the experience in one's own country (for example, if corruption prevents democracy operating effectively) may affect this judgement. Therefore, in the robustness we test whether results hold for a another more general survey question[47] (available for fewer survey waves). World Values Survey data begins in the 1980s and we pool data into a cross section due to insufficient observations in some region–year cells to generate reliable variation over time.

the polity2 variable is used as this is more suited for time series analysis.

[46] Specifically, the question asks respondents to say whether having a democratic political system is a (1) very good, (2) fairly good, (3) fairly bad, (4) bad way of governing their country. The scale is reversed for our estimation so that a higher score reflects higher approval.

[47] This question asks respondents if they (1) agree strongly, (2) agree, (3) disagree or (4) strongly disagree whit this statement "Democracy may have problems but is better than any other form of government". Again, the scale is reversed for our estimation so that a higher score reflects higher approval.

Table 1.5.3: Universities and Democracy

Dependent variable: Approval of Democracy	(1)	(2)	(3)	(4)
15 year lagged ln(1+#unis/pop)	0.0294***	0.0257***	0.0231**	0.0230**
	(0.00934)	(0.00960)	(0.00946)	(0.00997)
Male		0.0376***	0.0338***	0.0337***
		(0.00477)	(0.00468)	(0.00468)
Age (years)		0.00177***	0.00222***	0.00221***
		(0.000300)	(0.000302)	(0.000302)
Married		-0.00119	-0.00420***	-0.00407***
		(0.00127)	(0.00126)	(0.00123)
Children		-0.00696***	-0.00342*	-0.00348*
		(0.00200)	(0.00196)	(0.00194)
Employed		0.0173***	0.0239***	0.0239***
		(0.00551)	(0.00616)	(0.00613)
Income scale		0.0116***	0.00540	0.00562*
		(0.00339)	(0.00329)	(0.00323)
Degree			0.135***	0.135***
			(0.00775)	(0.00768)
Student			0.0854***	0.0856***
			(0.0116)	(0.0116)
Observations	138511	138511	138511	138511
# clusters	693	693	693	693
Country and year dummies	yes	yes	yes	yes
Geographic controls	no	no	no	yes

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. OLS estimates, 54 countries. Standard errors are clustered at the regional level. Region controls include latitude, inverse distance to ocean, malaria ecology, ln(oil and gas production) 1950-2010 and a dummy for if a region contains the country's capital city. "Employed" is a dummy=1 if the individual is full, part time, or self-employed.

Table 1.5.3 shows the results of these regressions.[48] We start with a simple correlation between our measure of university density lagged by 15 years from the survey year, controlling for country and year fixed effects (column (1)).[49] This shows that there is a highly significant association between university presence in a region and approval of a democratic system. The relationship is robust to including a host of individual demographic characteristics (column (2)) and education (column (3)). The result that one's own education is positively related to approval of democracy is consistent with Chong

[48] This analysis is carried out on 58 of the 78 countries in our core sample, where World Values Survey data are available. World Values Survey data are available for Nigeria which is in our core sample, but it was not possible to map the regions to the regions used in WHED due to the fact that both sources used very aggregated but different regions.

[49] We explored different lag structures, and found that it takes time for universities to affect perceptions (see column (3) in Table 1.D.10 which shows a smaller positive, but insignificant effect of five year lagged university density on democratic approval). By contrast, on the full sample of countries there appear to be no effects for longer lags. When we consider the sub-sample of OECD countries where the results are stronger we see that the effects are similar in magnitude and significance for the 30 year lag.

and Gradstein (2009). But the result that local universities matter over and above an individual's education suggests that they may be a mechanism whereby democratic ideals spillover from those who have had direct contact with universities, or there is some kind of direct diffusion of ideas from universities into their surrounding regions.[50] Column (4) adds our standard geographic controls. While data constraints mean it is not possible to account for any potential impact of this type of mechanism on growth, this analysis suggests that institutions could be part of the story, albeit on a longer term basis.

1.5.4 Demand

Could our results simply be driven by a mechanical impact of universities on regional GDP? Students and staff in a university consume more goods and services. Including changes in population in our regressions (lagged, and contemporaneous) should have largely controlled for the possibility that universities simply contribute to growth through a mechanical demand channel associated with people coming into the region. Moreover, showing that our university coefficient remains significant after including changes in human capital (see Table 1.5.1) should also address the concern that the effects are simply driven by higher earners entering the region.

To the extent that university finance comes from inside the same region, there should be no mechanical demand effect as this should already be netted off. For example, in the US, states have historically provided more assistance to tertiary institutions and students: 65 per cent more on average than the federal government over the period 1987 to 2012, though now the share is more equal.[51] But if university finance comes from outside the region this could also result in higher GDP per capita as the university purchases goods and services within the region (including paying salaries to staff and support services).

We think it unlikely that the regressions are merely capturing this type of effect. The initial shock to region GDP associated with the new university is likely to occur in the year it is founded (when transfers begin, and include capital and set up costs), and the level effect should be captured by lagged regional GDP which we control for in the regressions. Ongoing transfers may rise incrementally over the years as the university

[50] Further supporting this, we find that the result survives dropping students and graduates from the regression entirely (see Table 1.D.10 for more robustness tests and further discussion).

[51] This difference has narrowed in recent years as state spending declined since the financial crisis, and federal investments grew sharply. Today the total expenditure is similar, though spending categories differ: state funding focuses more on general running expenditure and federal funding on research and student grants. For detail, see an analysis of federal and state funding of higher education in the US by Pew Charitable Trusts, http://www.pewtrusts.org/en/research-and-analysis/issue-briefs/2015/06/federal-and-state-funding-of-higher-education

increases its size and scope, but we might expect the largest effect on growth would be in the initial years rather than in the subsequent five year period. Furthermore, the evidence of university spillovers from other regions (Table 1.4.4) also suggests demand is not the main mechanism.

Notwithstanding these arguments, we carry out a simple calculation to show that even under very generous assumptions, direct effects are unlikely to explain a large portion of our results. We use the hypothetical experiment of a new university of 8,500 students and 850 staff opening in the average region of our dataset. We estimate the effects of the transfer into the region assuming that all the costs of our new university are met from sources outside the region, and that these are spent within the region. We assume that the average cost per student is $10,000, and therefore the cost for a university of 8,500 students is $85 million. With a university of constant size, building up year-group enrolments over four years, there would be no effect in the following five year period. If we assume total enrolments grow by 5% per year, we can explain around 15% of the regression coefficient on universities.[52]

1.5.5 Summary on Mechanisms

In summary, it appears some of the effects of university growth on GDP growth work via human capital and innovation channels, though the effects of these are small in magnitude. In addition, universities may affect views on democracy but this appears to be on a longer term basis. We have shown that the university coefficient is not merely driven by demand effects.

1.6 Conclusions

This paper presents a new dataset on universities in nearly 1,500 regions in 78 countries since 1950. We have found robust evidence that increases in university presence are positively associated with faster subsequent economic growth. A 10% increase in the number of universities is associated with over 0.4% higher GDP per capita in a region. This is even after controlling for regional fixed effects, regional trends and a host of other confounding influences. The benefit of universities does not appear to be confined to the region where they are built but spills over to neighbouring regions, having the strongest

[52] For further detail, see Appendix.

effects on those that are geographically closest. Using these results, we estimate that the economic benefits of university expansion are likely to exceed their costs.

Our estimates use sub-national time series variation and imply smaller effects of universities on GDP than would be suggested from cross sectional relationships. But we believe our effects underestimate the long-run effect of universities through building the stock of human and intellectual capital which are hard to fully tease out using the panel data available to us. We reiterate that the coefficients on universities are conditional correlations as we do not have compelling instrumental variables to establish causality. Nevertheless, in our view the empirical evidence here does suggest some effect of universities on growth.

Understanding the mechanisms through which the university effects works is an important area to investigate further. We find a role for innovation and human capital supply although these appear to be small in magnitude, and show that the university effects do not appear to be driven by demand or transfers into a region. Better data on the flow of business-university linkages, movements of personnel and other collaborations would help in unravelling the underlying mechanisms. In addition, focusing on the relationships between universities and local economic performance in individual countries where better causal designs and richer university data is available would be a valuable extension.

We provide suggestive evidence that universities play a role in promoting democracy, and that this operates over and above their effect as human capital producers. Exploring the extent to which this may account for part of the growth effect is another important area for future research.

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1.A Data Appendix

1.A.1 WHED Coverage

WHED contains data on 185 countries (which includes 176 countries plus 9 administrative regions/dependencies: Hong Kong, Macao, Curaçao, French Guyana, French Polynesia, Guadeloupe, Martinique, New Caledonia and Reunion). We cross-check the 176 countries to a full list of independent states (from the US State Department [53] and find that there are only 16 more independent states not included in the database. These are Antigua and Barbuda, Comoros, Djibouti, Dominica, Eritrea, Grenada, Kosovo, Micronesia, Nauru, Palau, Saint Lucia, Saint Vincent and the Grenadines, Sao Tome and Principe, Seychelles, Solomon Islands and South Sudan.

WHED contains information on higher education institutions that offer at least a post-graduate degree or a four year professional diploma. It therefore excludes, for example, further education institutions in the UK or community colleges in the US and may be thought of as a sample of "higher quality" universities.

We compare the country totals in WHED as at 2010 to data from "Webometrics"[54], a source where higher education institutions (including ones that would not qualify for inclusion in WHED) are ranked by their "web presence". This source puts the total number of universities worldwide at 23,887 in 2015 (part of this difference will be due to growth over the 2010-2015 period). In the results section, we discuss a robustness check where we drop countries from our regressions with a very large divergence between the two sources.

1.A.2 Validating Our Approach

Our approach for calculating university presence by region uses the founding dates of universities to determine the number of universities that were present at any particular date. We consider that a "university" is founded on this initial founding date, even if it was a smaller higher education institute or college at that date. This is often the case, but our approach is reasonable since only the better quality institutions are likely to subsequently become universities. Furthermore, there are many cases where a number of universities or higher education institutes were merged together into what is today recorded as one university in WHED. Our approach avoids the apparent reduction that would occur in

[53] http://www.state.gov/s/inr/rls/4250.htm
[54] http://www.webometrics.info/en/node/54

such cases if we were merely counted the number of institutions present at any given date.

One key concern with this strategy is that it would not be suitable in a world where university exits are commonplace. Say a number of universities were present in the past and closed down before WHED 2010. A region could have actually seen a fall in universities, but our method would not capture this since it includes only surviving universities. Anecdotally we know that the period since the 1960s has been one of university growth across the globe, but we investigate this issue further in order to gain more comfort on the validity of our approach. We do this by obtaining historical records of the universities and higher education institutions present in the 1960s, and assess whether significant numbers of these are missing from WHED 2010.

The appropriate sources are the predecessors to WHED: "The International Handbook of Universities" (1959, published by the IAU annually); "American Universities and Colleges" (1960, published by The American Council on Education) and "The Yearbook of Universities of the Commonwealth" (1959, published by the Association of Universities of the British Commonwealth). As the name suggests, the "American Universities and Colleges" yearbook contains fully fledged universities, but also smaller colleges (including religious institutions), many of which would not be included in WHED today. The international handbook lists universities and other institutions not considered of "full university rank" separately. We include all of these institutions because the distinction is not consistent between countries – for example in France, these latter institutions contain all the grandes écoles which are considered to be of very high quality but are outside the framework of the French university system; and in China only one institution is listed as a full university while other institutions include a number of institutions with the name "university". The Commonwealth yearbook contains only fully fledged universities.

The main exercise we carry out is to name match between 1960 yearbooks and WHED 2010. There are 2,694 institutions listed across 110 countries in the three yearbooks in 1960, this compares with 5,372 institutions (in 132 countries) which according to WHED 2010 were founded pre 1960 – this is higher because WHED counts universities from the date they are founded, even if they are not founded as a fully-fledged university (as discussed above). The country level correlation of the number of universities present in 1960 in the two sources is 0.95. The matching process involves a number of iterations: exact matching, "fuzzy" matching, and manual matching. The process is complex because name changes and mergers are commonplace, therefore internet searches on Wikipedia or university websites were necessary. Where an institution was found to have been merged into a university that is present in WHED 2010 we considered it a match. The results of this process are summarised in Table 1.D.11. We find that university closure is extremely rare, and we only find evidence of this in the US, where 33 small (mostly religious) colleges are present in the 1960 yearbook and were found to have closed down, mainly due to bankruptcy. 155 institutions worldwide were found to still be in existence but not be listed in WHED. This was usually because they do not meet the WHED listing criteria (a university that offers at least a four year degree or postgraduate courses). Indeed, of the 155 institutions in this category, 115 were not considered fully fledged universities in 1960, and 33 of the remaining 40 were US colleges (mostly religious).

Based on these facts, we believe that it is reasonable to use the WHED founding dates as an (albeit imperfect) basis for a time series of university presence by region.

1.A.3 Describing Country Level University Growth in Selected Countries

This section gives an historical overview of the diffusion of universities from the 1880s in four advanced economies: France, Germany, the UK and US, and two emerging economies: India and China. We compare the timing of historical university expansions to growth and industrialisation (see Figure 1.C.5 for a measure of industrialisation over time in the UK, US, France and Germany sourced from Bairoch (1982)). This analysis provides a visual "sense-check" for the thesis developed by Mokyr (2002) that the building and dissemination of knowledge played a major role in the Industrial Revolution.

In the United Kingdom, universities have been established in waves: the "Ancient universities" starting with Oxford in 1100s were the first seven universities which were founded before 1800. Then a number of universities were chartered in the 19th Century, followed by the "Red Brick" universities before World War I. A large expansion occurred after World War II, around the time of the influential Robbins Report into Higher Education (Robbins, 1963). Former polytechnics were converted to universities in 1992, but in our data these higher education institutions are counted from when they opened in their original form. These waves can be seen in the university density line as shown in Figure 1.C.6, Panel A, which also plots national GDP per capita data (from Maddison), suggesting that the first expansions coincided with industrialisation in the 1800s (Figure 1.C.5 shows that industrialisation picked up from the 1830s in the UK). The raw university count trend is shown in Panel B.

In the US, the first university was Harvard, founded in 1636. By the time of the American Revolution there were nine colleges modelled on Oxford and Cambridge in England. However these were very small, exclusive and focused on religion and liberal arts. At that time, there were no law or medical schools, so one had to study these subjects in London. It was Thomas Jefferson who had a vision for state education, separate from religion, but this only took hold after the Civil War with the land grant colleges. This sharp rise in university density can be seen in Figure 1.C.7. Industrialisation in the US began to pick up in the 1860s (see Figure 1.C.5). University density reached much higher levels than in Britain: at 13 universities per million people in 1900 versus just over 2 in the UK. The difference is that in the US, density came down again as population growth outpaced the opening of new universities which continued to grow as shown in Panel B; though the downward trend did slow during the post war period (we can see the slight kick in university numbers from the 1950s in Panel B). However, the fall in university density must be considered in the context that over the same period, university size has also been increasing in the US and (this can be seen in Figure 1.C.8 and in our analysis on enrolments). Furthermore, there has been a sharp rise in "Community Colleges" in the US, which provide college access qualifications, and are not counted in our dataset.

In France, Figure 1.C.9 shows that university density really started picking up in the 1800s with the opening of the "Grande Écoles" which were established to support industry, commerce and science and technology in the late 19th Century. Indeed industrialisation in France was more gradual, and started picking up in the late 1880s, early 1900s. The next dramatic increase in universities numbers and density occurred in the 1960s during de Gaulle's reforms of the French economy.

Cantoni and Yuchtman (2014) discuss the opening of the first universities in Germany following the Papal schism in the late 14th Century. However, during the 1800s, Figure 1.C.10 shows that university density actually fell, as population growth outpaced the gradual increases in university numbers which can be seen in Panel B. Historically, Germany had a low share of college graduates as higher shares of the population were educated via the apprenticeship system. A deliberate push to expand university education began in the 1960s, with new public universities founded across the country (Jäeger, 2013). This was motivated by the need to compete in technology and science against the backdrop of the Cold War; but also social reasons, namely the notion that education is a civil right to be extended beyond the elites, and is crucial for democracy.

China and India saw much later expansions as shown in Figure 1.C.11 and Figure 1.C.12. China started opening up to Western advances in science in the 1800s, and followed Soviet influence in the 1950s with centrally planned education. We can see a sharp rise in university density from the 1900s to 1960. The spike in the 1960s is due to the Cultural Revolution, when higher education institutions were shut down for 6 years, and all research terminated. When the universities were reopened, they taught in line with Maoist thought. It was from the 1980s that institutions began to gain more autonomy and when China began its rapid growth trajectory, though so far growth in universities has not outpaced population growth. In India, expansion occurred after independence in 1947. During the colonial era, the upper classes would be sent to England for education. The British Raj oversaw the opening of universities and colleges from the late 1800s, but university density only started rising more rapidly after 1947 and recently has picked up pace again. We note that the in both countries, there are around 0.4 universities per million people, which is still a lot lower than in the UK or US.

Finally, we note that in general, expansions in university numbers have been accompanied by increases in university size. As we saw in Figure 1.C.8 (using UNESCO data that are only available from 1970), university students normalised by population have been growing overall in the US and the UK since the 1970s (with a dip in the late 1990s in the US) and more recently in China and India.

1.A.4 Case Studies of University Expansion in Selected European Countries

As three case studies we consider European countries that undertook largescale expansions in the 1960s and 1970s, and where decisions over the geographical roll-out of universities appear to be unrelated with expectations of a region's economic growth prospects. First, the UK undertook a large expansion in the 1960s, around the time of the influential Robbins Report on Higher Education (Robbins, 1963). One key motivation was to develop UK science and technology in response to Soviet advances (Barr, 2014). The so-called 'plate glass' universities (Beloff, 1968) were created on greenfield sites outside small or medium-sized towns and away from large population or industrial centres. This was in contrast with previous universities which had typically emerged "bottom up", starting life as colleges to meet local needs (often founded by industrialists) and upgrading to university status later (Shattock, 2012). Students were recruited nationally and grants were also administered at the national level by the "University Grants Committee".

As a second case study, we look at West Germany (Rüegg, 2010) where a high number of university openings took place in the early 1970s. Here key objectives were to improve equality of opportunity and the modernisation and democratisation of society (Jäeger, 2013). Within the country, locational decisions were primarily driven by the objective of achieving an equal distribution of higher education. There was also a belated response to the rise of East Germany and the threat from what was perceived as rapid technological advances in the Soviet bloc.

Thirdly, in Finland, there was a large increase in the number of universities and their geographical spread in the 1960s and 1970s. The expansion of the university sector was closely linked with regional development policies (Rüegg, 2010), but locational decision-making processes were drawn out and uncertain, with committees split over favoured locations (Toivanen and Väänänen, 2016). It appears that decisions were primarily influenced by political forces rather than economic activity of different areas.

1.B Further Results

1.B.1 Specification and Sample Checks

In Table 1.D.3, we show that our regressions are robust to a series of checks. We perform these on columns (5) and (7) of Table 1.4.2. In row (2) we conservatively cluster standard errors at the country level, to account for correlation between the errors of regions within the same country over time. While the standard errors rise a little, the association between lagged university growth and GDP per capita growth remains significant at the 1% level.[55] In row (3) we weight the regression by the region's population as a share of total country population, in case low density regions (which might be outliers) are affecting the results. Again, this weighting has little effect on the university coefficient. In row (4) we include country-year dummies instead of lagged country-level GDP per capita, to control for time varying factors at the country level (including national income) that may affect both university growth and GDP per capita growth (for example a general increase in funding for higher education, or a change in national government). This does reduce the coefficient, but it is still highly significant. In row (5) we control for the current (as well as lagged)

[55] We also estimate these regressions using Driscoll-Kraay standard errors to allow for cross-sectional dependence in a panel. The results are still highly significant (at the 1 per cent level) and given that such methods are not intended for panels with small T and large N (our core sample has T=13 and N=1,498) we prefer to stick with region-level clusters in our core specifications. We note that our results are robust also to clustering at the country level which is a more conservative specification as it allows the standard errors in one region-year to be correlated with standard errors in any other region-year within the same country.

change in population to address the concern that the effect of the university is simply to pull in more people to the region, who spend or produce more and hence raise GDP per capita growth. Our university effect remains strong and therefore it does not appear to be driven by population growth. Row (6) uses growth in university density (universities per million people) instead of university count, with very similar results. We prefer to use the university count in our core analysis, with controls for population growth, as changes in university density can be driven either by the numerator (universities) or the denominator (population) and can be more difficult to interpret.

We then perform a few checks to see whether regions with no universities, or regions getting their first university are driving the results. Row (7) of Table 1.D.3 drops regions which never have a university in the sample period, and row (8) drops region-years with zero universities, and the coefficients remains unchanged. To make sure our results are not driven by extreme university growth observations we do two things. Row (9) drops region-year observations where a region opens its first university, and in row (10) we winsorise the top and bottom five per cent of university growth which both strengthen the results.[56] Row (11) uses similarly winsorised GDP per capita growth as the dependent variable, which dampens reduces our coefficient slightly but it still significant at the 1% level. In row (12) we show that the results are not sensitive to dropping observations where we have interpolated GDP per capita. To address measurement problems in terms of missing founding dates, in row (13) we include a dummy for regions where more than five percent of the universities have missing founding dates. Finally, we explore whether the definition of university in WHED (i.e. only institutions that offer four year courses or postgraduate degrees) may be a problem, in the sense that there may be some countries that have a larger share of institutions outside this category which could be important for growth. For this purpose, we compare the most recent university numbers in our database to an external source, Webometrics.[57] Row (14) shows that our results are robust to dropping the 29 countries where there are more than double the number of institutions in Webometrics compared to the WHED listing.

[56] In further robustness checks we also explore if there are any heterogeneous effects for regions opening their first universities by interacting the dummy with the university growth variable. The coefficients on both the dummy and interaction term are not significantly different from zero.

[57] http://www.webometrics.info/en/node/54

1.B.2 Simulation of the Effects of a New University on the Average Region's Human Capital and GDP

To assess the plausibility of the magnitudes identified in the main text we consider some quantitative calculations of university expansion.

To look at a representative case we take the average region in the dataset as summarised in Table 1.2.1: a population of just under 3 million, GDP per capita of $13,056 (and hence GDP of $39 billion), a college share of 7%, average years of education of 7.37, and just under 10 universities.

We assume that a new university with a capacity of 8,500 students is opened in the region. We believe that a university of 8,500 students a generous size for a new university, based on to average enrolments in our sample countries over the years where country level enrolments data are available.[58] The annual intake of students is 2,125, so the university is at capacity in four years. We assume it takes four years to graduate with a bachelors degree and a staff student ratio of 10,[59] so that there are 850 staff present at the university at full capacity. We assume that students enter the region to begin studying, and stay in the region post graduation, adding to its human capital stock. We keep the university size constant for the five year period following its opening. We assume that staff enter the region in the first year and remain there. We assume that the typical graduate has 18 years of education.

This experiment involves adding one university to an existing stock of 10 universities, which represents a 10% increase over a five year period, or an average of 2% per year. To compare to our regression results, which represent the impacts of a 1% increase in universities, we need to double the regression coefficients. Our core coefficient on universities in column (7) of Table 1.4.2 is 0.0467. This implies that a 1% increase in the number of universities is associated with a 0.0467% increase in GDP per capita in the subsequent 5 years. Therefore the implied increase in GDP per capita following a 2% change would be around 0.09%.

The impact of a 1% increase in universities in the previous period on college share

[58] We obtained total tertiary education enrolments from UNESCO which is available since the 1970s, and divided by the number of universities in our data, to get the average number of universities by country in each year where the data are available. The average over the period is just under 8,200. Obviously, this will represent existing as well as new universities. Moreover, this is likely to be an overstatement since, as we previously discussed, not all tertiary institutions are included in WHED. The average growth rate in students per university implied by this country level data over the period is 2.5% per annum.

[59] This is a generous assumption. In the UK, for example, staff-student ratios range between 9 and 25 (see http://www.thecompleteuniversityguide.co.uk/league-tables/rankings?o=Student-Staff%20Ratio)

from Table 1.5.1, column (8) is an increase in college share of 0.004, which represents 0.4 percentage points since college share is measured as a fraction. Therefore we double this to 0.008 to compare with the experiment. Similarly, the impact on years of education is a 0.02% increase, so we double this to 0.04%.

Using this simple example we generate impacts on college share and years of education growth in the next five year period and compare these to the predictions from our regressions.

Our calculation involves a churning out of 2,125 new graduates per year and this results in an average annual rise in college share of 0.0006 (or 0.060 percentage points) in the next five year period. This is actually smaller than the 0.008 implied from our regressions, and could be due to more inward migration of skilled people following the opening of universities, which we do not capture controlling only for population changes. On the other hand the implied average annual rise in years of education is 0.09% which is more similar to the 0.04% implied by the regressions (which, as we noted are based on a different sample from the college share regressions).

While there are differences here, our simulation shows that the effects on human capital even with generous assumptions about the size of a new university, will be relatively small. This is in line with what we find in the regression analysis.

1.B.3 Demand Effects of Universities

Using this same example of the representative region, we can simulate the demand effects of university expansion. If the university is funded from outside the area then GDP may increase mechanically as demand from a university (e.g. rent, supplies, building and maintenance) and its staff and students boost the local economy.

We assume that the cost per student in our new university is $10,000 per year, which is likely to be an overestimate of the average university in our sample.[60] For a university of 8,500 students this implies total costs of $85 million. Since this represents annual costs, we assume that the transfer continues in each subsequent year. Therefore the uplift to GDP will be felt only in the *initial* years. Assuming that total enrolments stay fixed at 8,500 over the five years following university entry (which is the key period we use for our regressions), there would be *no* uplift to GDP per capita in that period. Alternatively, if we

[60] In 2011 the OECD average tertiary education spending by educational institutions was $13,958 (see Education at a Glance 2014: OECD Indicators, Indicator B1). On average OECD countries spent 41% of GDP per capita per student in 2011. $ 10,000 represents 77% of GDP per capita in our average region-year ($ 13,056).

assume enrolments are growing by 5% per year[61] this would only account for around 15% of calculated effect of a 2% increase in universities implied by our baseline specification (0.09%).

1.B.4 Universities and Democratic Approval

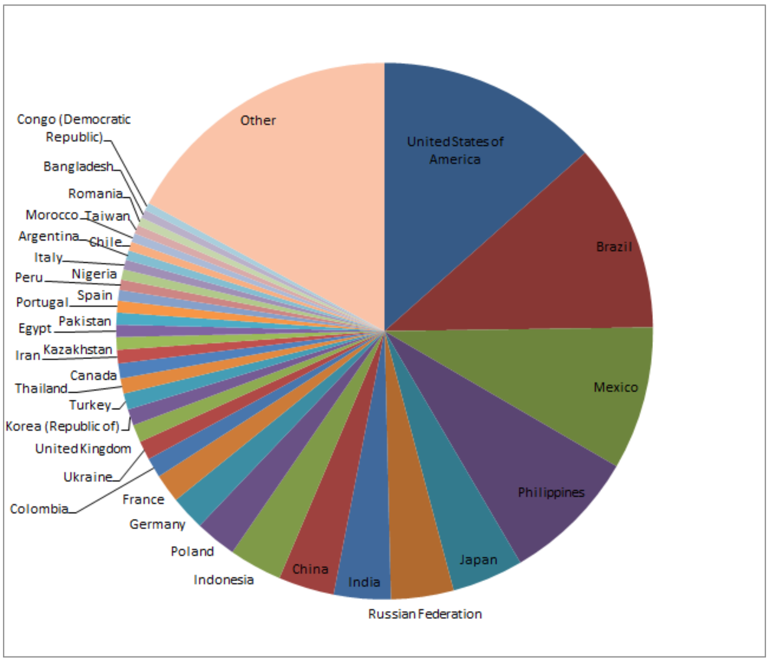
Figure 1.C.3 Panel E shows that there is a positive and significant correlation between country level polity scores and university density, in the cross section (for 2000). Figure 1.C.13 also shows that there is a positive and significant correlation between the change in university density and change in polity scores over 1960-2000.

Table 1.D.10 reports a number of robustness tests around the regressions of approval of democracy on lagged university presence reported in Table 1.5.3. Column (1) repeats Table 1.5.3 column (4). Column (2) shows that this effect might be slightly stronger for OECD countries, as an interaction term between an OECD dummy and the lagged university presence is positive, but it is not significant at conventional levels. Column (3) shows that the main result is much smaller in magnitude and insignificant for 5 year lagged university presence, and actually negative for a 30 year lag. Column (5) shows that our main result can be closely replicated using a different survey measure for approval of democracy, "democracy is best" which asks respondents whether they agree with the statement that democracy is better than any other form of government. Column (6) does not include country fixed effects. This shows that the positive relationship we find between universities and approval of democracy is valid within countries. Across countries, factors not controlled for in these regressions (for example, levels of corruption) appear to influence the result. We investigated which countries appear to be driving this negative relationship and found, for example, that the Philippines (a country with high levels of corruption) has high university density but low approval of democracy. Column (7) clusters at the country level and significance holds. Column (8) weights by population, to account for the fact that some regions with low population may have less representative responses. Column (9) drops students and graduates and the main result gets stronger. Finally, column (10) shows that the results are robust to estimation using an ordered-probit model.

[61] The average growth rate in students per university implied by the UNESCO country level enrolments data over the period since the 1970s is 2.5% per annum.

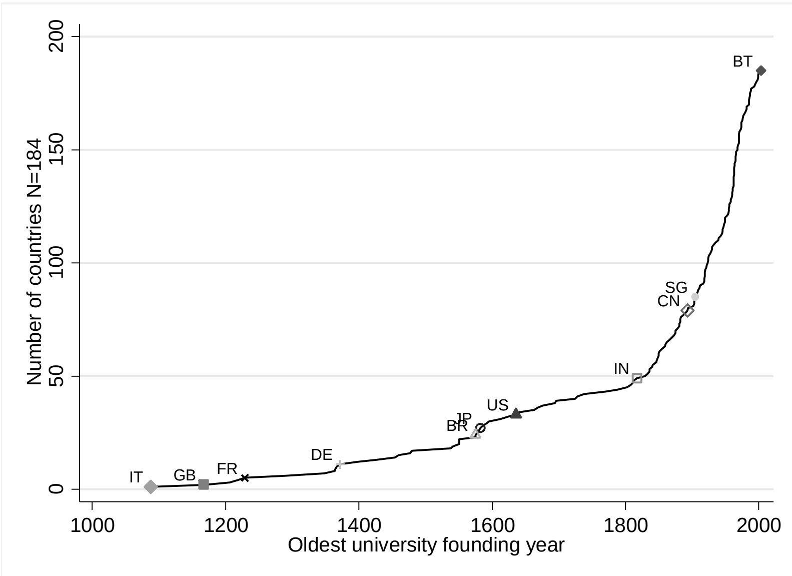
1.C Appendix Figures

Figure 1.C.1: Location of Universities in 2010



NOTES: Pie chart shows the share of worldwide universities in each country, as at 2010. Source: WHED.

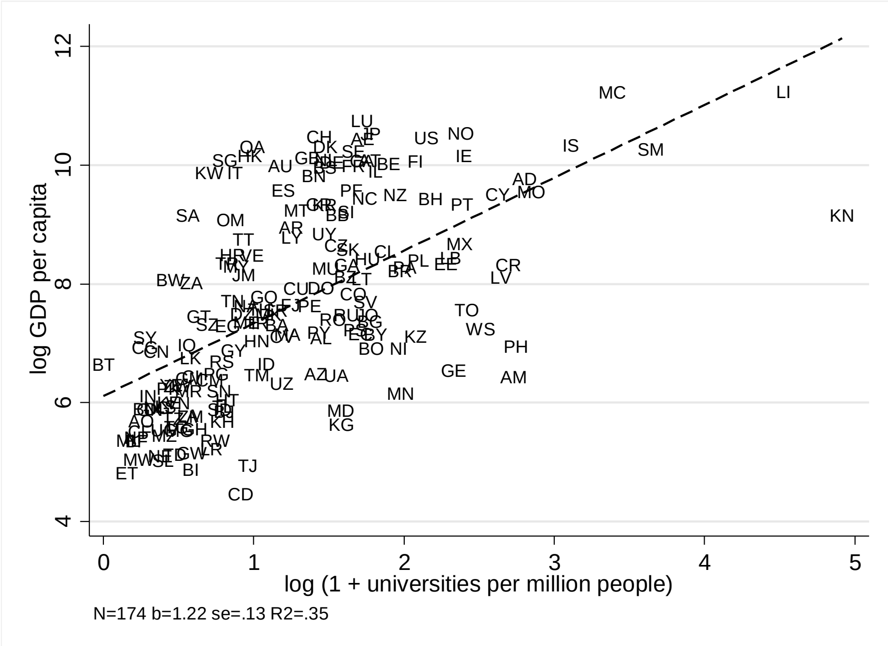
Figure 1.C.2: Diffusion of Universities Across Countries



NOTES: This chart shows the total number of countries that have universities over time, with some key countries marked in the year they opened their first universities marked. Source: WHED.

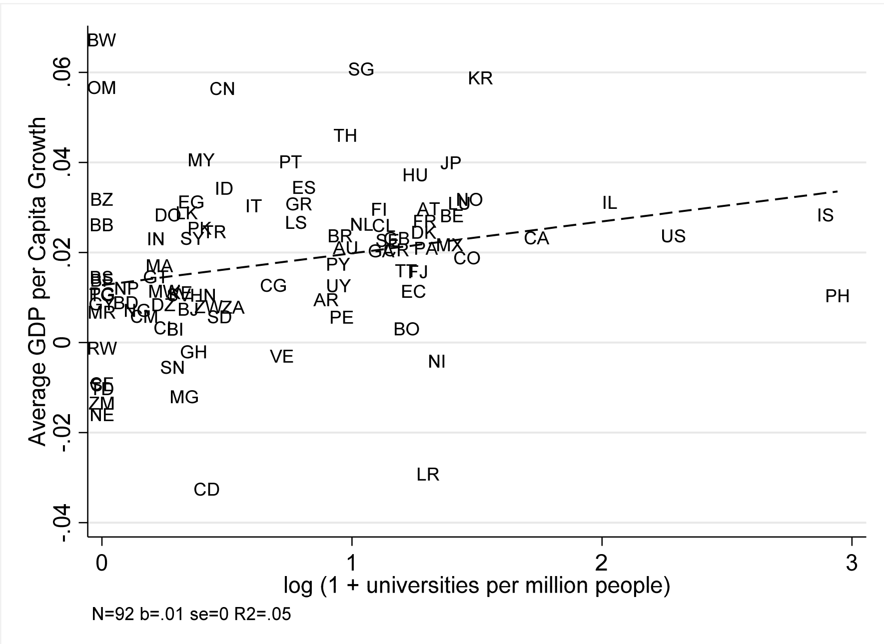
Figure 1.C.3: Country Level Correlations

A: Universities and income in 2000



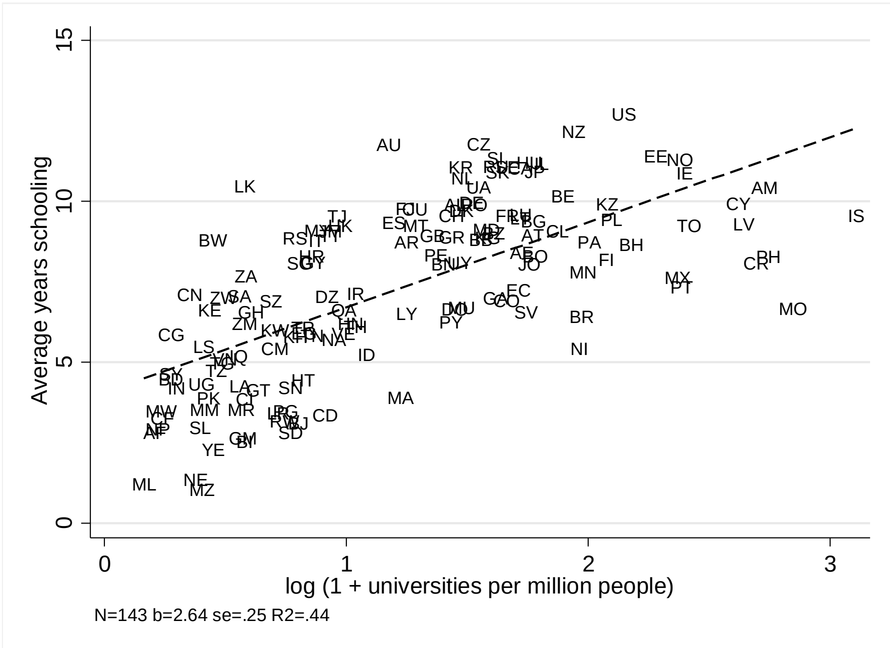
NOTES: Each observation is a country in 2000. Source: WHED and World Bank GDP per capita.

B: Universities in 1960 and GDP per capita growth (1960-2000)



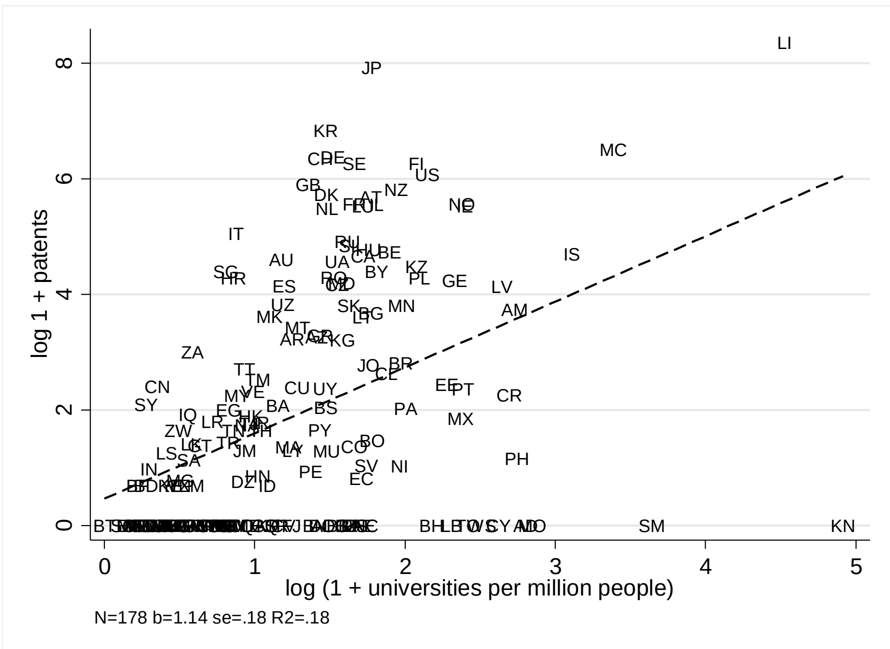
NOTES: Each observation is a country. Average annual growth rates over the period 1960-2000 on the y axis. Source: WHED and World Bank GDP per capita.

C: Universities and average years of schooling in 2000



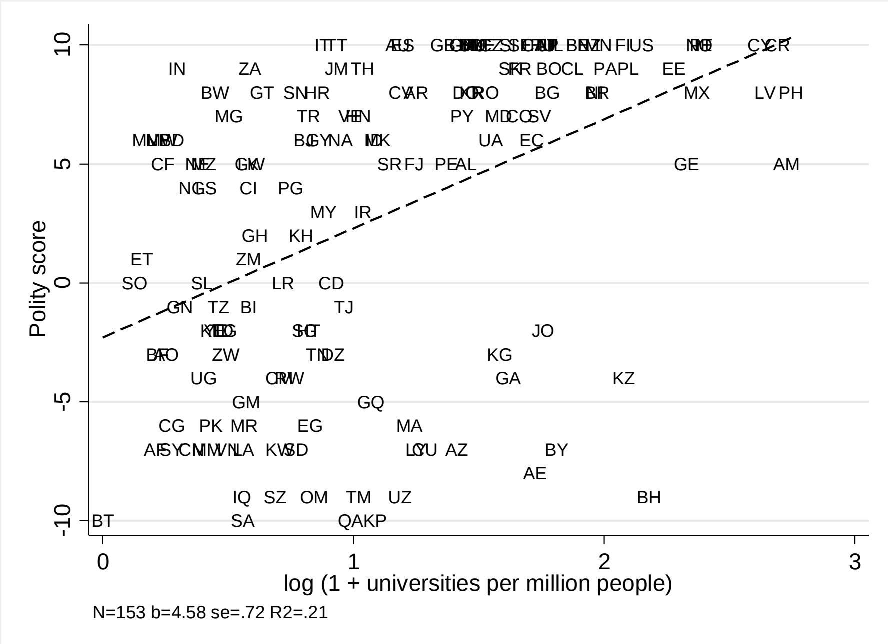
NOTES: Each observation is a country in 2000. Source: WHED and years of schooling obtained from Barro-Lee dataset

D: Universities and patents in 2000



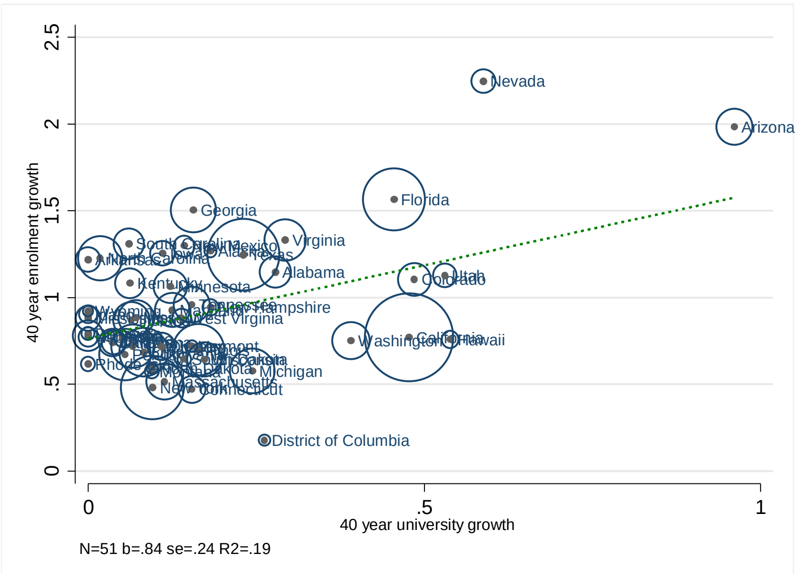
NOTES: Each observation is a country in 2000. Source: WHED and patents from WIPO

E: Universities and democracy in 2000



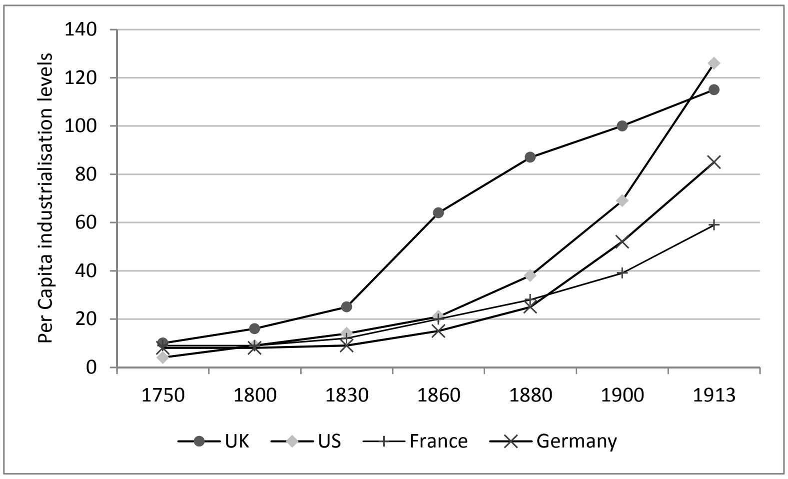
NOTES: Each observation is a country in 2000. Source: WHED and Polity2 scores from Polity IV project

Figure 1.C.4: Growth in US Enrolments vs Growth in Universities



NOTES: Each observation is a region (US state), weighted by the region's share in total US population in 2010. 40 year growth relates to the period 1970-2010. Dropping Arizona, b=0.62 and se=0.28. Source: WHED and NCES.

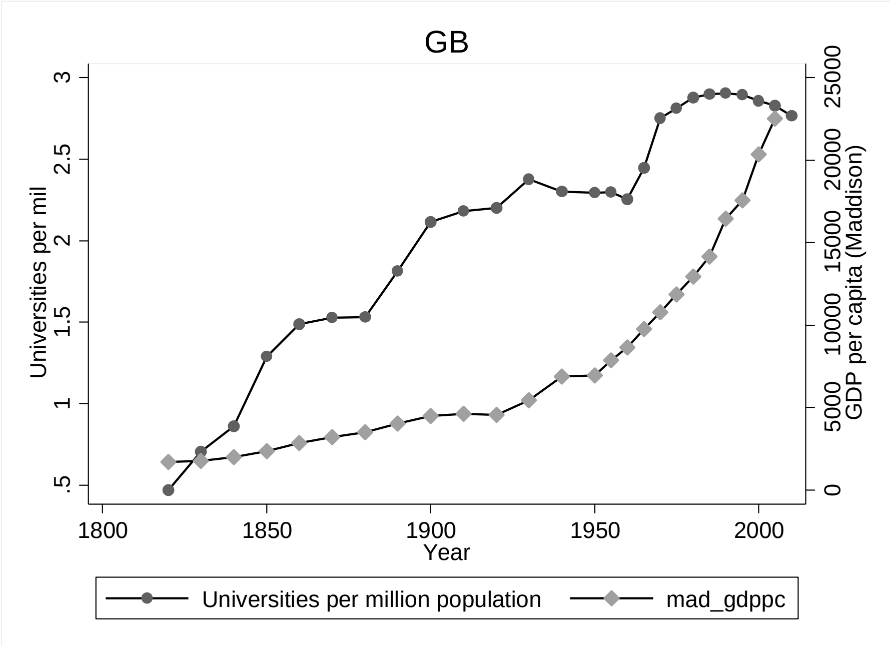
Figure 1.C.5: Per Capita Industrialisation Levels, 1959-1913 (UK1900=100)



NOTES: Graph based on Table 9, Bairoch (1982); taken from Baldwin (2012)

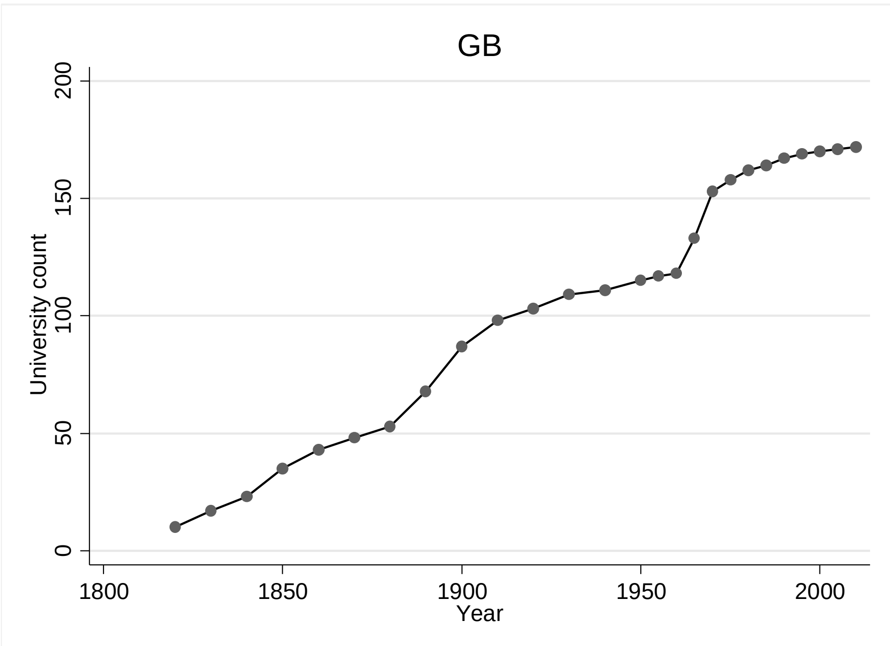
Figure 1.C.6: Universities and Industrialisation in the UK

A: University density and GDP per capita trends



NOTES: This chart shows the evolution of university density (universities per million people) and GDP per capita over time. Source: WHED and Maddison GDP per capita data.

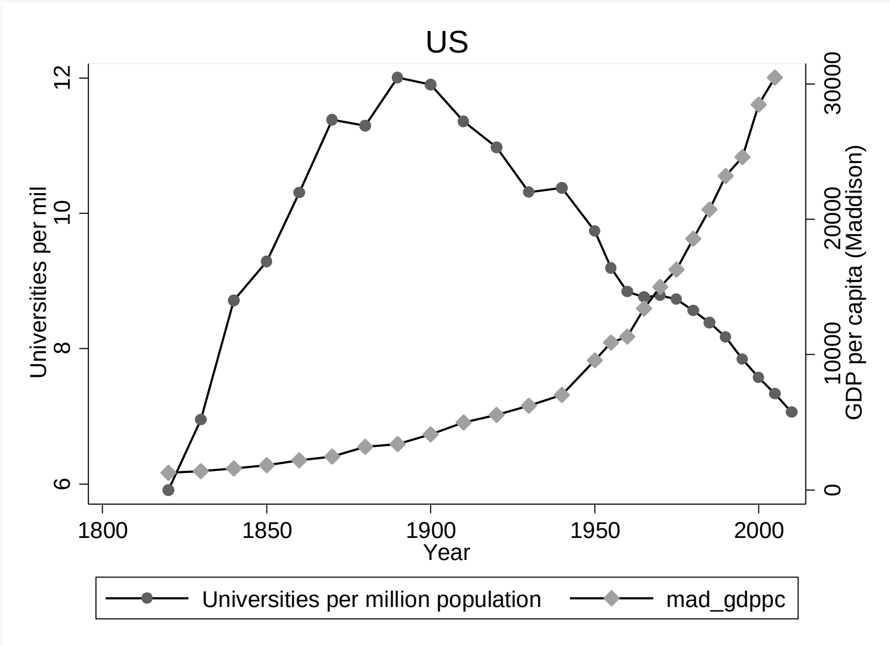
B: University count trend



NOTES: This chart shows the evolution of university count over time. Source: WHED

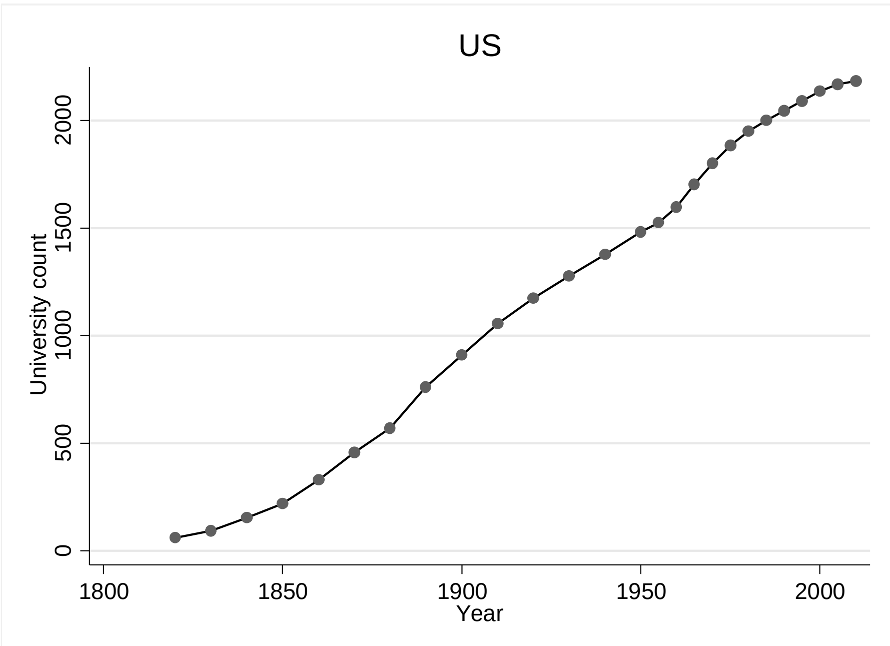
Figure 1.C.7: Universities and Industrialisation in the US

A: University density and GDP per capita trends



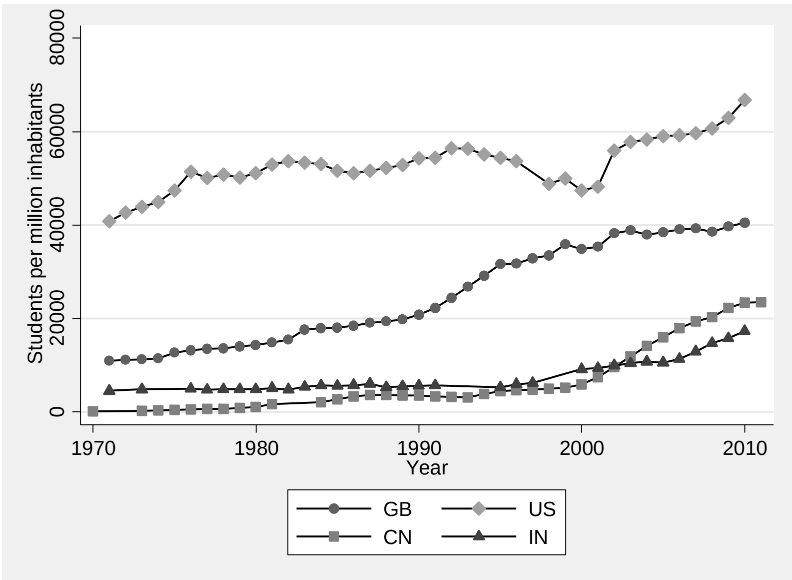
NOTES: This chart shows the evolution of university density (universities per million people) and GDP per capita over time. Source: WHED and Maddison GDP per capita data.

B: University count trend



NOTES: This chart shows the evolution of university count over time. Source: WHED

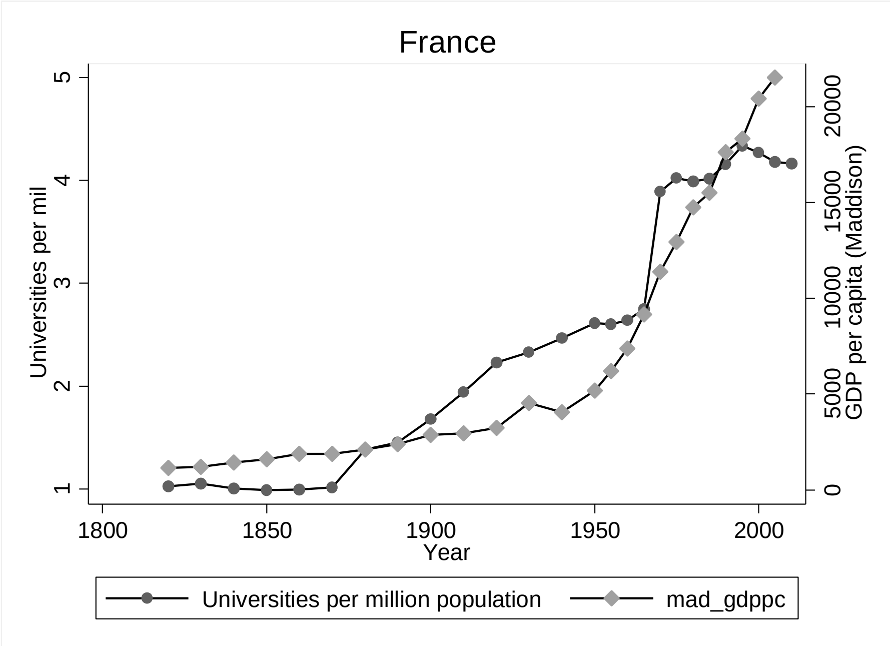
Figure 1.C.8: Trends in Student Numbers Normalised By Population



NOTES: Number of students in tertiary education per million inhabitants. Source: UNESCO

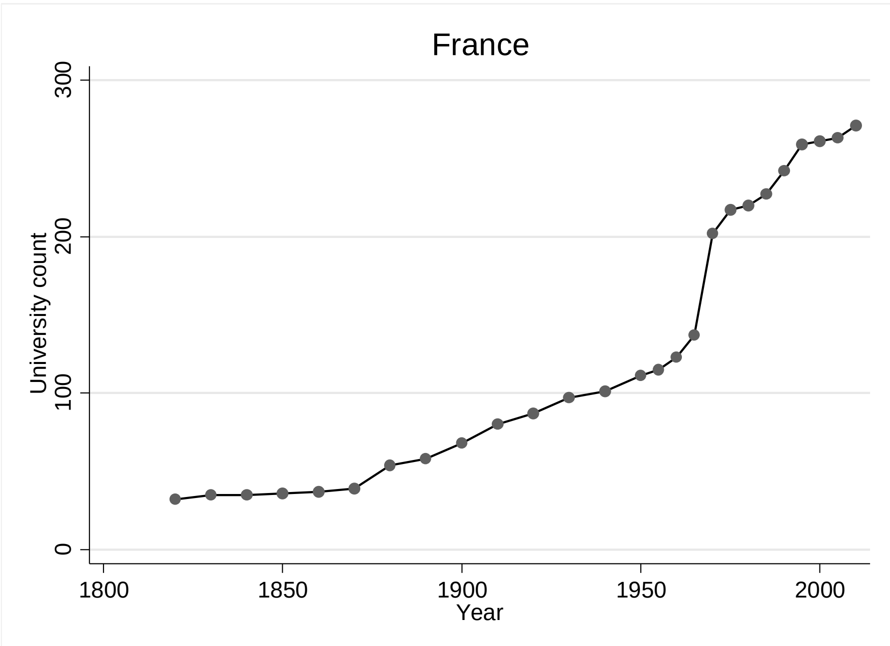
Figure 1.C.9: Universities and Industrialisation in France

A: University density and GDP per capita trends



NOTES: This chart shows the evolution of university density (universities per million people) and GDP per capita over time. Source: WHED and Maddison GDP per capita data.

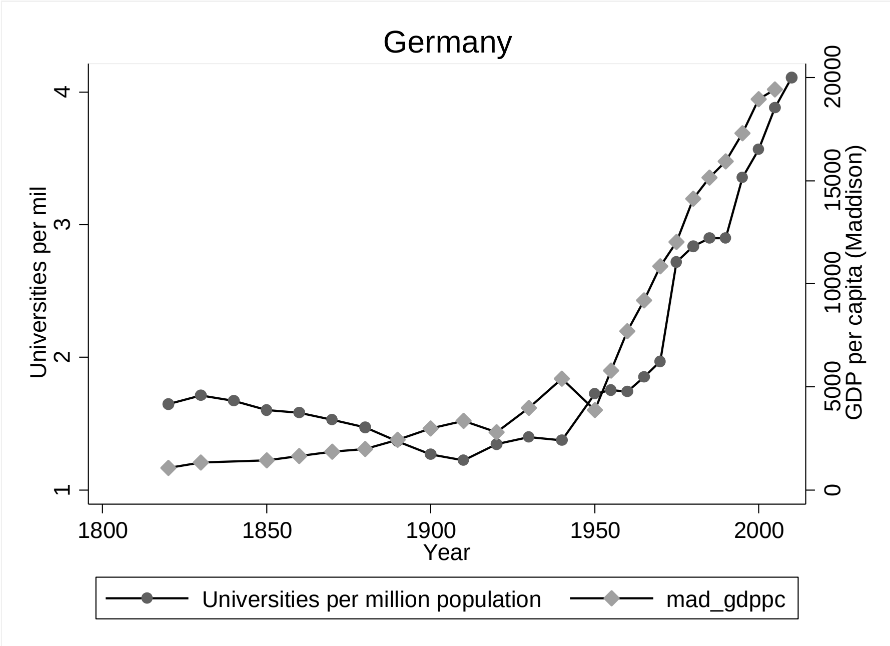
Panel B: University count trend



NOTES: This chart shows the evolution of university count over time. Source: WHED

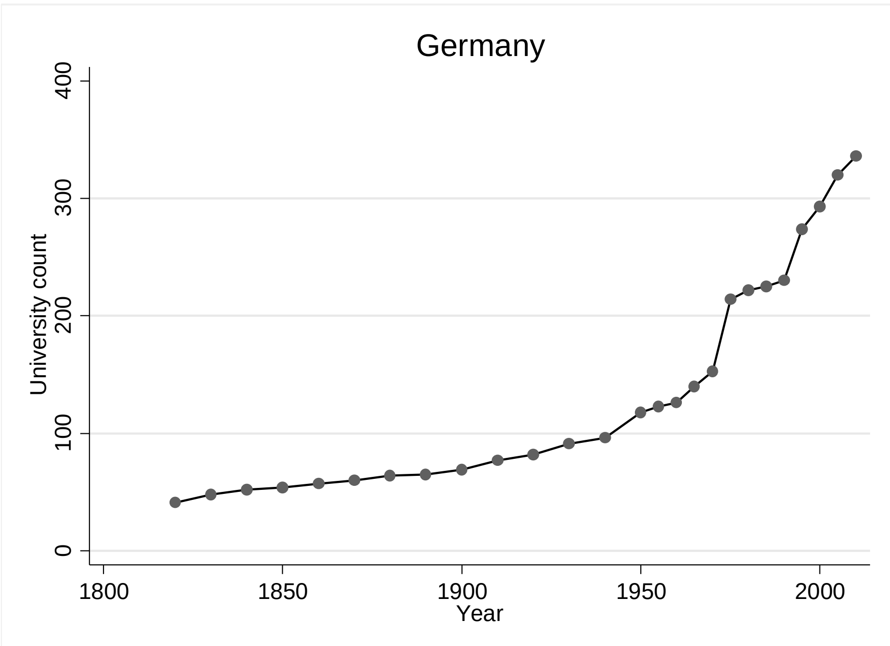
Figure 1.C.10: Universities and Industrialisation in Germany

A: University density and GDP per capita trends



NOTES: This chart shows the evolution of university density (universities per million people) and GDP per capita over time. Source: WHED and Maddison GDP per capita data.

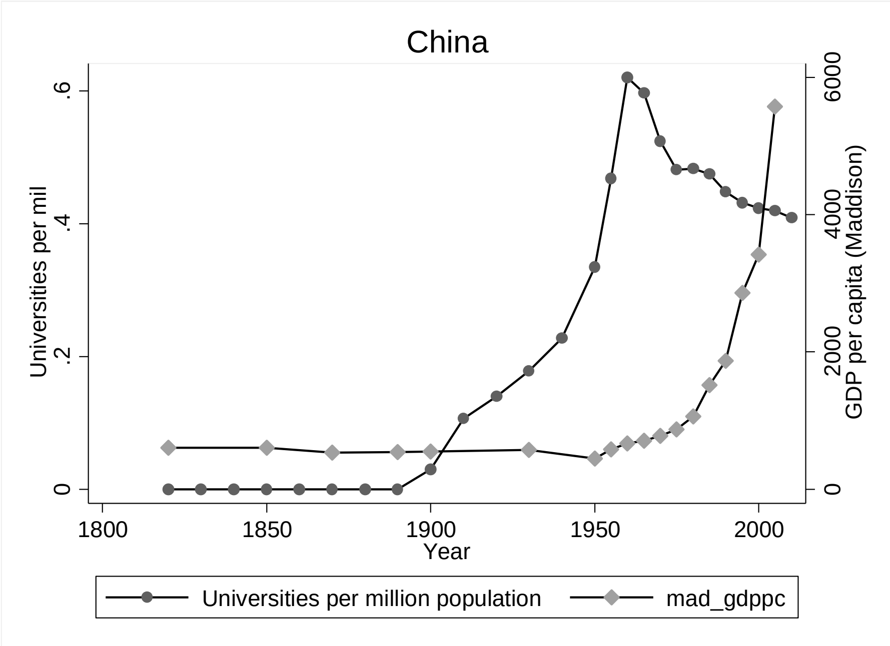
B: University count trend



NOTES: This chart shows the evolution of university count over time. Source: WHED

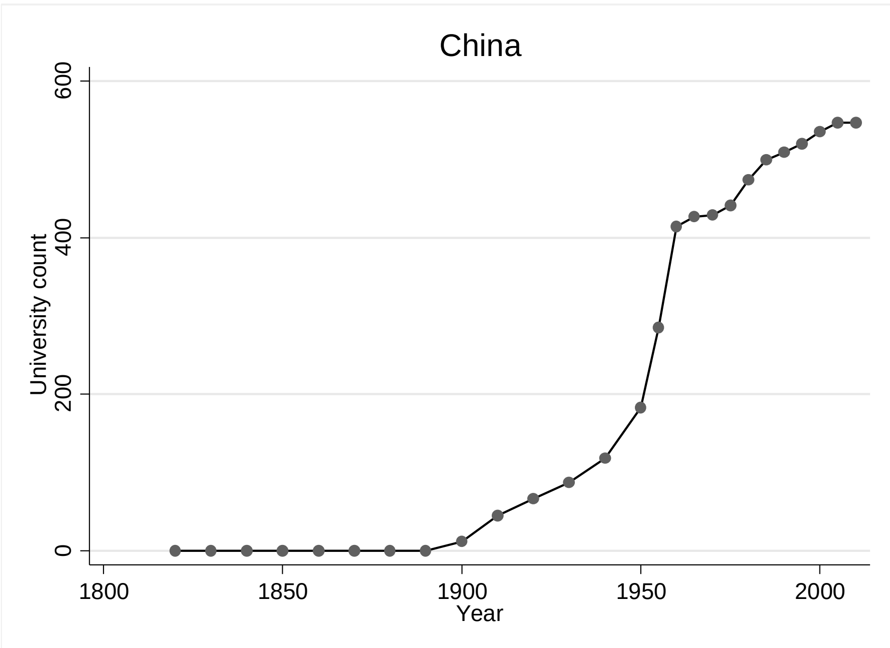
Figure 1.C.11: Universities and Industrialisation in China

A: University density and GDP per capita trends



NOTES: This chart shows the evolution of university density (universities per million people) and GDP per capita over time. Source: WHED and Maddison GDP per capita data.

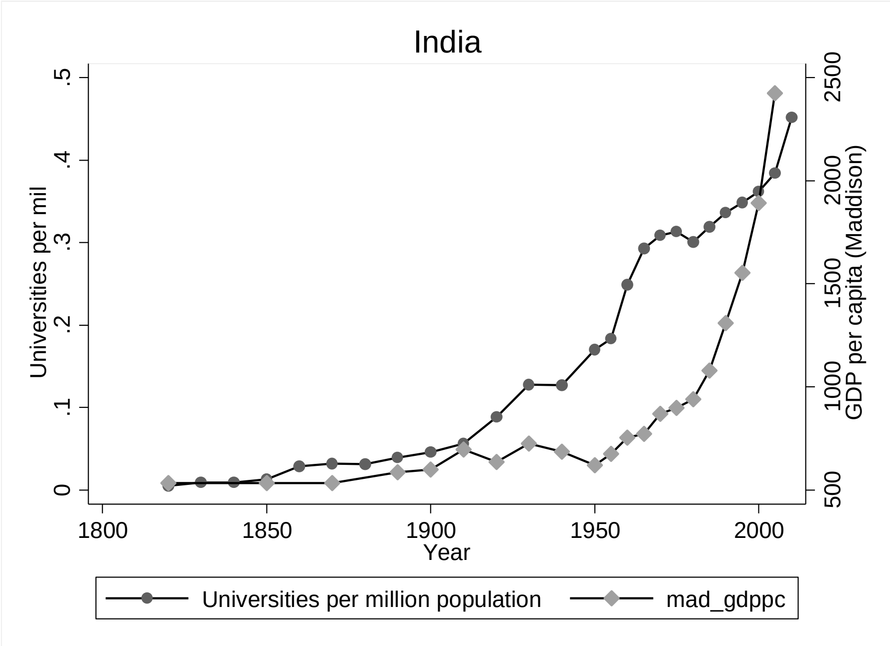
B: University count trend



NOTES: This chart shows the evolution of university count over time. Source: WHED

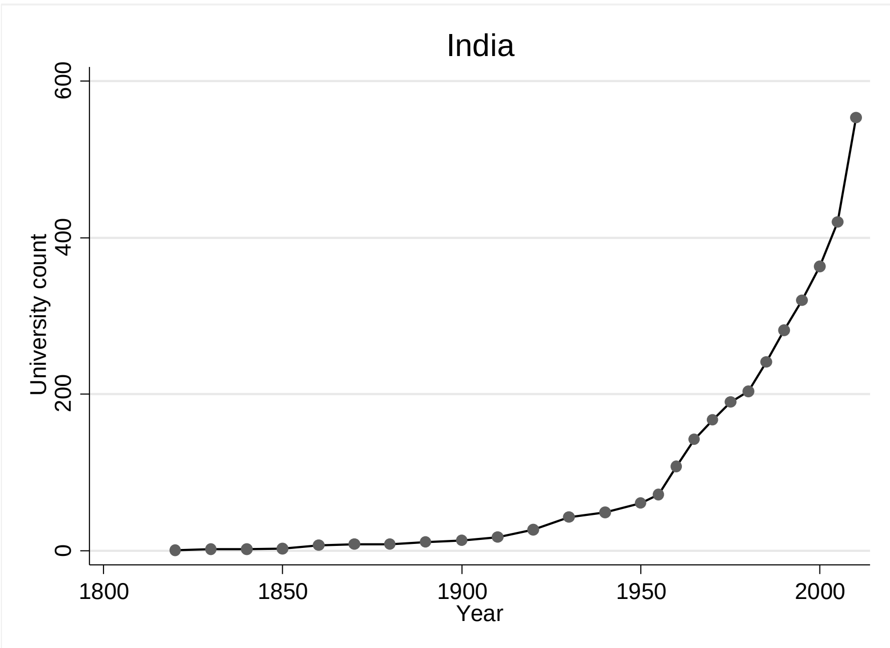
Figure 1.C.12: Universities and Industrialisation in India

Panel A: University density and GDP per capita trends



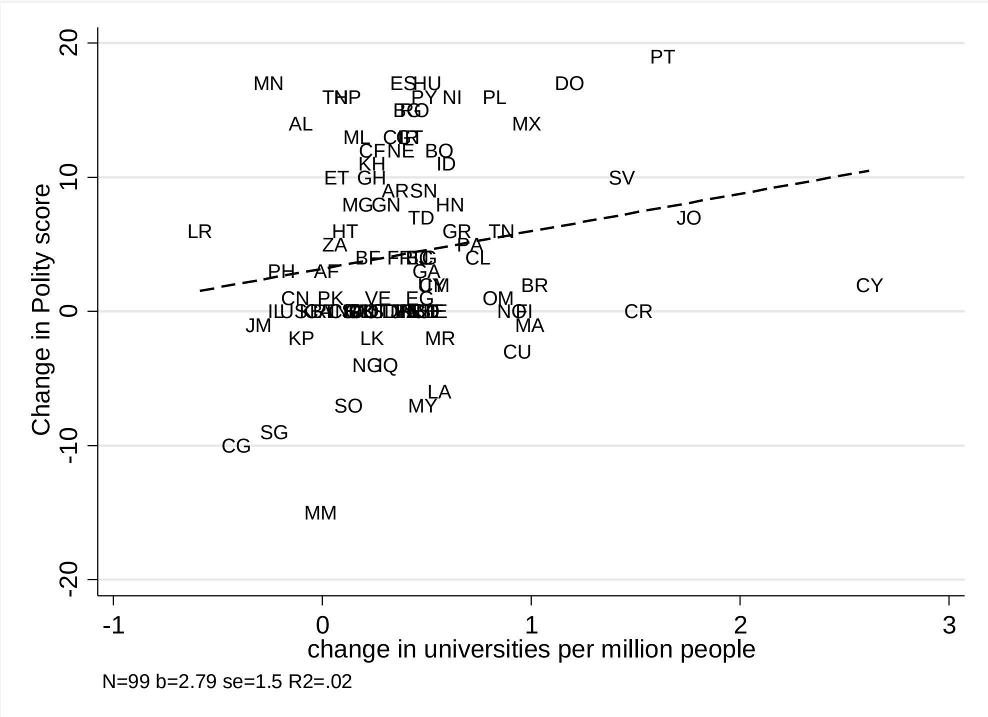
NOTES: This chart shows the evolution of university density (universities per million people) and GDP per capita over time. Source: WHED and Maddison GDP per capita data.

Panel B: University count trend



NOTES: This chart shows the evolution of university count over time. Source: WHED

Figure 1.C.13: Change in Universities and Change in Democracy



NOTES: Each observation is a country in 2000. Source: WHED and Polity 2 variable from Polity IV

1.D Appendix Tables

Table 1.D.1: Full Results of Baseline Covariates Specification

Dependent variable: Regional Growth in GDP per capita	(1)
Lagged growth in #universities	0.0444***
	(0.0105)
Lagged level of regional GDP per capita	-0.0127***
	(0.00131)
Lagged level of country GDP per capita	-0.0213***
	(0.00422)
Lagged level of population	-0.0855**
	(0.0387)
Lagged growth in population/100	-0.113***
	(0.0385)
Dummy for capital in region	0.0110***
	(0.00168)
Latitude	-0.000318***
	(0.0000875)
Inverse distance to ocean	0.00456
	(0.00373)
Malaria ecology	0.000736**
	(0.000292)
log(oil and gas production) 1950-2010	0.000293**
	(0.000142)
Observations	8128
# clusters	1498

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. This table replicates Table 1.4.2, column (5) to show the geographic controls. Note, ln(oil and gas production) 1950-2010 is not normalised by population

Table 1.D.2: Distributed Lag Specifications

Dependent variable: Regional Growth in GDP per capita	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A: Full sample							
Current growth in #universities		-0.00794	-0.00505	-0.0126	-0.0128	-0.0186	0.00205
		(0.0111)	(0.0111)	(0.0120)	(0.0131)	(0.0153)	(0.0168)
5 year lagged growth in #universities	0.0467***		0.0455***	0.0593***	0.0537***	0.0587***	0.0858***
	(0.0107)		(0.0107)	(0.0119)	(0.0128)	(0.0134)	(0.0156)
10 year lagged growth in #universities				0.0223**	0.0261**	0.0170	0.0306*
				(0.0108)	(0.0119)	(0.0136)	(0.0171)
15 year lagged growth in #universities					0.00566	-0.00321	-0.00587
					(0.0111)	(0.0134)	(0.0177)
20 year lagged growth in #universities						0.00627	0.00893
						(0.0150)	(0.0187)
25 year lagged growth in #universities							0.0249*
							(0.0139)
Observations	8128	9246	8128	6863	5635	4604	3638
B: US, UK, FR, DE							
Current growth in #universities		0.00101	0.0168	0.0474**	0.0854***	0.0269	-0.00456
		(0.0204)	(0.0212)	(0.0227)	(0.0263)	(0.0396)	(0.0432)
5 year lagged growth in #universities	0.0509***		0.0572***	0.0864***	0.104***	0.143***	0.132***
	(0.0157)		(0.0176)	(0.0200)	(0.0188)	(0.0184)	(0.0332)
10 year lagged growth in #universities				0.0301	0.0367*	0.0612***	0.0756***
				(0.0189)	(0.0206)	(0.0220)	(0.0229)
15 year lagged growth in #universities					0.0135	0.0271	0.0270
					(0.0258)	(0.0287)	(0.0260)
20 year lagged growth in #universities						0.0474**	0.0405**
						(0.0215)	(0.0183)
25 year lagged growth in #universities							0.0171

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Dependent variable:Regional Growth in GDP per capita	(1)	(2)	(3)	(4)	(5)	(6)	(7)
							(0.0191)
Observations	1023	1116	1023	930	837	744	651
C: Rest							
Current growth in #universities		-0.00691	-0.00425	-0.0148	-0.0170	-0.0149	0.0161
		(0.0116)	(0.0117)	(0.0127)	(0.0138)	(0.0157)	(0.0169)
5 year lagged growth in #universities	0.0482***		0.0473***	0.0619***	0.0572***	0.0611***	0.0946***
	(0.0112)		(0.0113)	(0.0126)	(0.0135)	(0.0141)	(0.0164)
10 year lagged growth in #universities				0.0210*	0.0262**	0.0192	0.0391**
				(0.0115)	(0.0126)	(0.0143)	(0.0181)
15 year lagged growth in #universities					0.00238	-0.00700	-0.00138
					(0.0117)	(0.0142)	(0.0194)
20 year lagged growth in #universities						0.00176	0.0105
						(0.0163)	(0.0207)
25 year lagged growth in #universities							0.0283*
							(0.0152)
Observations	7105	8130	7105	5933	4798	3860	2987

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Column (1) is replicates column (7) from Table 1.4.2. The subsequent columns add contemporaneous and further lagged growth in universities, and corresponding population growth. The level of population at the furthest lag is also controlled for.

Table 1.D.3: **Summary of Robustness Tests**

		Coefficient, lagged uni growth		N
		Covariates	Region Trends	
(1)	Benchmark	0.0444***	0.0467***	8128
		(0.0105)	(0.0107)	
	A. Specification			
(2)	Cluster at country level (78 clusters)	0.0444***	0.0467***	8128
		(0.0138)	(0.0162)	
(3)	Population weights	0.0410***	0.0427***	8128
		(0.0126)	(0.0133)	
(4)	Country-year fixed effects	0.0281***	0.0226**	8128
		(0.0103)	(0.00992)	
(5)	Control for current population change	0.0439***	0.0451***	8128
		(0.0104)	(0.0106)	
(6)	University density	0.0304***	0.0292***	8128
		(0.00904)	(0.00865)	
	B. Sample issues			
(7)	Drop regions that never have uni	0.0432***	0.0473***	6642
		(0.0105)	(0.0107)	
(8)	Drop regions before they have uni	0.0424***	0.0447***	6041
		(0.0108)	(0.0109)	
(9)	Drop first university observations	0.0507***	0.0623***	7897
		(0.0133)	(0.0142)	
(10)	Winsorize university growth	0.0612***	0.0642***	8128
		(0.0146)	(0.0147)	
(11)	Winsorize GDP per capita growth	0.0342***	0.0355***	8128
		(0.00775)	(0.00795)	
(12)	Un-interpolated GDP per capita	0.0485***	0.0468***	5312
		(0.0134)	(0.0143)	
	C. Measurement issues			
(13)	Dummy, >5% missing founding dates	0.0421***	0.0467***	8128
		(0.0106)	(0.0107)	
(14)	Country total check (Webometrics)	0.0528***	0.0578***	5357
		(0.0130)	(0.0130)	

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. The dependent variable in all rows is regional growth in GDP per capita. Row (1) replicates column (5) and column (7) from Table 1.4.2.

Table 1.D.4: University Growth As the Dependent Variable

Dependent variable: Regional Growth in Number of Universities	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged growth in regional GDP per capita	-0.0116	-0.00554	-0.00766	-0.00984	-0.00995	-0.0298	-0.0292
	(0.0144)	(0.0179)	(0.0180)	(0.0182)	(0.0167)	(0.0194)	(0.0208)
Lagged growth in country GDP per capita		-0.0167	-0.0162	-0.0132	-0.0741***	-0.0538**	-0.0422
		(0.0237)	(0.0237)	(0.0239)	(0.0221)	(0.0237)	(0.0260)
Lagged growth in population			-0.0570	-0.0704	-0.101*	-0.114**	-0.137**
			(0.0537)	(0.0540)	(0.0557)	(0.0553)	(0.0655)
Lagged level of population/100				-0.696**	1.970***	2.016***	2.562***
				(0.292)	(0.400)	(0.408)	(0.503)
Lagged #universities					-0.0484***	-0.0486***	-0.0545***
					(0.00328)	(0.00327)	(0.00355)
Lagged level of regional GDP per capita						0.00942**	0.00756
						(0.00422)	(0.00472)
Lagged level of country GDP per capita						-0.00826*	-0.0152**
						(0.00475)	(0.00602)
Lagged years of education							-0.00333***
							(0.00122)
Lagged growth in years of education							0.0825**
							(0.0335)
Observations	7746	7746	7746	7746	7746	7746	6506
# clusters	1489	1489	1489	1489	1489	1489	1458

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. All columns include region and year fixed effects, and standard errors clustered by region. Column (1) is simple correlation between regional growth in universities and the lagged growth in regional GDP per capita. Columns (2) to (6) include the additional variables shown. Column (7) includes the lagged level and lagged growth in years of education for the subsample where these measures are available. Levels of GDP per capita and population are in natural logs.

Table 1.D.5: Heterogeneity by Continent

Dependent variable: Regional growth in GDP per capita	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All	US, UK, FR, DE	Other Europe, Canada	Latin America	Asia	Africa
Lagged growth in #universities	0.0467***	0.0509***	0.00399	0.0872***	0.0339	0.116
	(0.0107)	(0.0157)	(0.0109)	(0.0202)	(0.0260)	(0.0925)
Lagged level of regional GDP per capita	-0.0776***	-0.0569***	-0.0606***	-0.0708***	-0.0963***	-0.124***
	(0.00478)	(0.00849)	(0.00553)	(0.00796)	(0.00908)	(0.0218)
Lagged level of country GDP per capita	0.0378***	-0.0518***	0.0195***	0.0269**	0.0590***	-0.0649
	(0.00611)	(0.0101)	(0.00732)	(0.0115)	(0.00995)	(0.0439)
Lagged level of population	-0.850**	-0.179	-2.201***	-1.709**	-1.997**	-4.373***
	(0.352)	(0.368)	(0.669)	(0.812)	(0.933)	(1.581)
Lagged growth in population	-0.183***	-0.0667	-0.527***	-0.189**	-0.139	0.108
	(0.0452)	(0.0890)	(0.0905)	(0.0922)	(0.0906)	(0.102)
Observations	8128	1023	2792	1821	2249	243
# clusters	1498	93	581	295	462	67

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Column (1) replicates column (7) from Table 1.4.2. The other columns carry out an identical regression, but restricting to the sample continent as labelled. Levels of GDP per capita and population are in natural logs. Latin America contains Mexico, Central America and South America. Asia contains Australia.

Table 1.D.6: Heterogeneity by Time Periods for Selected Country Groupings

Dependent variable: Regional growth in GDP per capita	(1)	(2)	(3)	(4)	(5)	(6)
		US, UK, FR, DE			Asia	
Sample	All	Pre-1990	Post-1990	All	Pre-1990	Post-1990
Lagged growth in #universities	0.0509***	0.0421**	0.0801*	0.0339	0.00387	0.0638*
	(0.0157)	(0.0178)	(0.0413)	(0.0260)	(0.0263)	(0.0351)
Lagged level of regional GDP per capita	-0.0569***	-0.103***	-0.0968***	-0.0963***	-0.131***	-0.135***
	(0.00849)	(0.0117)	(0.0185)	(0.00908)	(0.0126)	(0.0107)
Lagged level of country GDP per capita	-0.0518***	-0.0169	0.0224	0.0590***	0.0566***	0.0810***
	(0.0101)	(0.0152)	(0.0173)	(0.00995)	(0.0170)	(0.0158)
Lagged level of population	-0.00179	-0.00170	-0.0459***	-0.0200**	-0.0267*	-0.0671***
	(0.00368)	(0.00498)	(0.00989)	(0.00933)	(0.0145)	(0.0213)
Lagged growth in population	-0.0667	0.0441	0.00683	-0.139	-0.00126	0.0627
	(0.0890)	(0.0670)	(0.0573)	(0.0906)	(0.185)	(0.134)
Observations	1023	651	372	2249	841	1408
# clusters	93	93	93	462	297	462

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Column (1) carries out our core regression on the full sample for those countries. Columns (2) and (3) restrict to the time periods specified. Columns (4), (5) and (6) do similar for the Asian sample of countries (which includes Australia).

Table 1.D.7: Barro Regressions with Lagged Universities

Dependent variable: Regional growth in GDP per capita	(1)	(2)	(3)	(4)
Lagged #universities			0.00243***	0.00189**
			(0.000758)	(0.000755)
Lagged level of population/100			-0.235***	-0.200***
			(0.0679)	(0.0673)
Lagged level of regional GDP per capita	-0.0141***	-0.0178***	-0.0150***	-0.0184***
	(0.00142)	(0.00165)	(0.00148)	(0.00169)
Lagged level of country GDP per capita	-0.0361***	-0.0321***	-0.0356***	-0.0318***
	(0.00353)	(0.00373)	(0.00353)	(0.00372)
Lagged level of population density	-0.000562	-0.00109**	-0.000220	-0.000730
	(0.000418)	(0.000424)	(0.000482)	(0.000488)
Lagged years of education		0.00399***		0.00386***
		(0.000569)		(0.000570)
Observations	8010	8010	8010	8010
Adjusted R-squared	0.273	0.279	0.274	0.280
# clusters	1504	1504	1504	1504

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Column (1) replicates Gennaioli et al. (2014) Table (5), column (8), with geographic controls, year and country fixed effects, but omits years of education. There are more observations because we have interpolated GDP per capita in the sample (Gennaioli et al. (2014) only interpolate years of education and population). Column (2) adds years of education. Column (3) replicates column (1), but adds the five year lagged level of universities in a region, and lagged population. Column (4) then adds years of education to the specification in column (3). Standard errors are clustered at the regional level. The lagged number of universities is the natural log of 1 + the 5 year lagged number of universities. Levels of GDP per capita, population and population density are in natural logs. Years of schooling are not logged.

Table 1.D.8: Longer Difference Barro Regressions

Dependent Variable: Average annual GDP per capita growth	50 year differences		40 year differences		30 year differences	
	(1)	(2)	(4)	(5)	(6)	(7)
Lagged #universities	-0.000293	0.00344**	-0.000764**	0.00198	0.000266	0.00239**
	(0.000395)	(0.00150)	(0.000319)	(0.00128)	(0.000603)	(0.00105)
Lagged level of regional GDP per capita		-0.0125***		-0.00650***		-0.0127***
		(0.00239)		(0.00169)		(0.00164)
Lagged level of population		-0.00257*		-0.00208*		-0.000819
		(0.00142)		(0.00115)		(0.000875)
Change in population		0.0831		0.0223		-0.0625
		(0.0644)		(0.0564)		(0.0714)
Observations	188	188	250	250	464	464
Country fixed effects	no	yes	no	yes	no	yes

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. This table shows long differences to 2000: so columns (1) to (2) show regressions for the sample where data are available for the period 1950-2000; columns (3)-(4) show regressions for the period 1960-2000; and columns (5)-(6) show regressions for the period 1970-2000. Column (1) is a simple correlation of the average annual growth in regional GDP per capita over 1950-2000 on the natural log of 1+ the number of universities in 1950. Column (2) adds country fixed effects, the 1950 natural log of the level of regional GDP per capita, the 1950 natural log of the level of population, the 1950-2000 change in population and country fixed effects. Columns (3) and (4) do the same for the 40 year difference to 2000. Columns (5) and (6) do the same for the 30 year difference to 2000. More data are available in later years, so the samples are larger for the shorter long differences. Robust standard errors are shown in parentheses.

Table 1.D.9: Universities and Years of Education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Δ GDPpc	Δ GDPpc	Δ GDPpc	Δ GDPpc	Δ GDPpc	Δ GDPpc	Δ Years Educ.	Δ Years Educ.
Lagged growth in #universities	0.0467***	0.0587***	0.0568***	0.0571***	0.0559***	0.0574***	0.0534***	0.0216**
	(0.0107)	(0.0125)	(0.0124)	(0.0125)	(0.0124)	(0.0125)	(0.0140)	(0.00916)
Lagged growth in years of education			0.0734***		0.0625***	0.0617***		
			(0.0264)		(0.0240)	(0.0239)		
Current growth in years of education				0.0751*	0.0551	0.0819**		
				(0.0418)	(0.0389)	(0.0399)		
Lagged years of education						0.00203**		
						(0.000941)		
Lagged level of regional GDP pc	-0.0776***	-0.0877***	-0.0877***	-0.0877***	-0.0877***	-0.0878***		-0.0000889
	(0.00478)	(0.00642)	(0.00640)	(0.00643)	(0.00640)	(0.00636)		(0.00256)
Lagged level of country GDP pc	0.0378***	0.0210***	0.0195**	0.0208***	0.0196**	0.0195**		0.00206
	(0.00611)	(0.00795)	(0.00791)	(0.00796)	(0.00794)	(0.00790)		(0.00321)
Lagged level of population/100	-0.850**	-2.090***	-2.094***	-1.946***	-1.988***	-2.132***		-1.916***
	(0.352)	(0.475)	(0.470)	(0.469)	(0.468)	(0.458)		(0.290)
Lagged growth in population	-0.183***	-0.0449	-0.0498	-0.0448	-0.0490	-0.0442		-0.00102
	(0.0452)	(0.0504)	(0.0501)	(0.0505)	(0.0502)	(0.0504)		(0.0231)
Observations	8128	6117	6117	6117	6117	6117	6117	6117
# clusters	1498	1343	1343	1343	1343	1343	1343	1343

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Column (1) replicates column (7) from Table 1.4.2. Column (2) restricts to the sample for which the change in years of education is available. Column (3) drops the lagged growth in years of education. Column (4) adds the contemporaneous change in years of education. Column (5) includes both lagged and contemporaneous changes. Column (6) further adds the lagged level of years of education (unlogged). Column (7) regresses the change in years of education on the lagged growth in universities, with country dummies, but no other controls. Column (8) adds all the other controls.

Table 1.D.10: Robustness on World Values Survey Analysis

Dependent Variable: View of democracy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Approval	Approval	Approval	Approval	Best	Approval	Approval	Approval	Approval	Approval
15 year lagged ln(1+#universities per capita)	0.0230**	0.0137			0.0332**	-0.0525***	0.0230*	0.0547**	0.0291***	0.0398**
	(0.00997)	(0.0120)			(0.0163)	(0.0164)	(0.0120)	(0.0218)	(0.0110)	(0.0161)
OECD X 15 year lagged ln(1+#universities per capita)		0.0246								
		(0.0177)								
5 year lagged ln(1+#universities per capita)			0.0127							
			(0.00822)							
30 year lagged ln(1+#universities per capita)				-0.00212						
				(0.00913)						
Observations	138511	138511	138511	138511	48181	138511	138511	138511	100782	138511
# clusters	693	693	693	693	335	693	58	693	691	693
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS	weighted OLS	OLS	Oprobit
Standard errors clustered at	region	region	region	region	region	region	country	region	region	region
Country and year dummies	yes	yes	yes	yes	yes	no	yes	yes	yes	yes
Sample	all	all	all	all	all	all	all	all	drop students, graduates	all

NOTES: *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level. Column (1) replicates column (4) from Table 1.5.3. Column (2) includes an OECD dummy (not reported) and interaction between this and lagged university density. Column (3) is identical to column (1), but uses the five year lagged university density. Column (4) uses the thirty year lagged university density. Column (5) has a different dependent variable: the view that democracy is “best”. Column (6) omits country and year dummies. Column (7) clusters standard errors at the country level. Column (8) uses weighted OLS, weighting each region by its population as a share of the country’s total population. Column (9) drops graduates and students from the sample. Column (10) is estimated using an Ordered Probit model.

Table 1.D.11: Matching WHED and 1960 Yearbooks

Outcome	University	Other	Total
Match - exact	570	65	635
Match - fuzzy	653	138	791
Match - manual	384	696	1080
Not in WHED 2010	40	115	155
Death	33	0	33
Total	1680	1014	2694

NOTES: This table reports the outcome of the matching process between WHED and historical yearbooks, by universities and other types of institution.

Chapter 2

The Local Economic Impact of Universities: Evidence from UK Firms[1]

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2.1 Introduction

Universities are often regarded as key players in national and regional economic growth strategies, producing human capital via students graduating into the workforce, and generating innovations from their research activity. Since the 1990s, there has been increased focus also on the so-called "third mission", giving universities an explicit role in socio-economic development (Laredo, 2007). This has included the establishment of new functions such as technology transfer offices, science parks or incubator facilities that have sought to translate research into marketable innovations. Areas characterised by a high share of innovative industries and entrepreneurship, such as Silicon Valley in the US or the Cambridge cluster in the UK, surround universities and appear to benefit from agglomeration economies and associated knowledge spillovers.[2] This is something that policymakers seek to emulate in other geographical regions. The UK government's recently published industrial strategy lays out a vision for a "knowledge-led" economy, in which "'Innovation clusters' will form and grow around our universities and research organisations, bringing together world-class research, business expertise and entrepreneurial drive" (HMG, 2017).

While there is a large body of literature on universities and innovation spillovers,[3] fewer studies go on to link university research and innovation to local economic outcomes (Hausman, 2017; Kantor and Whalley, 2014; Aghion et al., 2009) and little is known about the impacts of universities on their local economies in more general terms (Valero and Van Reenen, 2018). Of key interest from a growth perspective is the extent to which universities stimulate start-up activity. While many start-ups stay small or go out of business after a few years, a small fraction become high growth firms or "gazelles" (Haltiwanger et al., 2017). Such firms are considered to be key drivers of job creation and productivity growth and are part of the dynamics of reallocation that characterise growth in advanced economies, but have been in decline in recent years.[4] Existing studies on the impact of universities on start-ups tend to be focused on specific manufacturing sub-sectors.[5] From a sectoral perspective, start-ups in the innovative high-tech sectors (across both

[2] For reviews of the literature see Carlino and Kerr (2015) or Henderson (2007).

[3] This literature begins with Jaffe (1989). See for example Jaffe, Trajtenberg and Henderson (1993), Anselin, Varga and Acs (1997), Belenzon and Schankerman (2013), and Andrews (2017).

[4] Decker et al. (2016) show that since 2000 there has been a decline in high-growth firms, especially those that are young. Calvino, Criscuolo and Menon (2018) show that there have been similar trends across 19 countries, including the UK.

[5] See for example Woodward, Figueiredo and Guimaraes (2006) who analyse the impact of university science and engineering research spending on start-ups in the US manufacturing sector in the 1990s. Other papers include Bania, Eberts and Fogarty (1993) and Zucker, Darby and Brewer (1998).

manufacturing and services) are of particular importance for future growth (Bakhshi et al., 2015).[6] In contrast, start-ups in less innovative sectors might include more "lifestyle" entrepreneurs who have no aspiration to significantly grow.[7]

In this paper, I examine how university expansion affects start-ups, employment and productivity in nearby local economies using panel data on UK firms and universities over the period 1997-2016. While I focus in particular on high-tech sectors, I also analyse impacts across other sectors of the economy. The core analysis is conducted at the level of small local areas (wards), and the main measure of university presence is the enrolments of students within a given radius (30km) of the ward centroid. University size is used as a proxy for university activity, since in general, a larger university might be expected to have a higher impact via graduates entering the labour market, and more staff and resource for research or other activities relevant for local industry.[8]

The key empirical challenge I face is the fact that university growth is unlikely to be random. A number of common factors affect the growth of both universities and local businesses. Furthermore, there may be direct feedback as successful local economies draw in more students. For example, changing local or regional development policies or other shocks are likely to be correlated with both university expansion and a growing economy, and areas with growing economies might attract more students or induce universities to expand. These issues imply that cross-sectional relationships between university activity and business outcomes are likely to be confounded. To address these endogeneity concerns, the analysis in this paper is based on a panel framework, with ward level fixed effects to control for time invariant factors that might be correlated with both university size and local economic performance. The university presence measure is based on the three year lag of enrolments to avoid the effects of contemporaneous demand shocks and create a plausible channel for enrolments to affect local economies (since most students enrolled at a British university should have graduated after three years). In addition, all regressions control for population within the same radius as students which should capture local demand shocks, and also control for the mechanical demand effects of students and university staff consuming goods and services in the local area.

[6] See Haltiwanger et al. (2017). Acemoglu et al. (2013) provide evidence that innovative activity tends to be concentrated in the high-tech sectors, and that within those sectors, high-growth firms are more likely to be young.

[7] See Hurst and Pugsley (2011).

[8] In this context, this measure is preferred relative to the simple count of universities (Valero and Van Reenen, 2018) since it reflects the scale of the university, and varies over time. The period since 1997 has not been one of significant entry of new universities in the UK, though a number of pre-existing higher education institutions have been upgraded to university status.

The analysis reveals the main effects of universities are at the extensive margin via the entry of new establishments, and in particular single-unit establishments, which I refer to as start-ups. Increased university presence generates modest but statistically significant growth in the number of start-ups in high-tech sectors, with a 1% rise in students enrolled within a 30km radius of a ward leading to a 0.09% increase in start-ups. These results are robust to a number of different assumptions on specification. While I focus on the high-tech sectors, I also show that there are positive effects in other services, including hospitality, retail and recreation which might grow differentially with an increased student population versus general population growth. In contrast, employment effects at the area level are positive but insignificant, and the average establishment size actually falls with increases in university size. This appears to be due to both the extensive margin (a composition effect due to the entry of smaller establishments) and the intensive margin (existing establishments getting smaller, in particular older, larger establishments) which could be evidence of a process of creative destruction. Ward level productivity analysis reveals that on average areas are not more productive when universities grow. This might be expected since areas with higher numbers of start-ups might also have depressed measured productivity due to lower mark-ups (Foster, Haltiwanger and Syverson, 2008). However, I find that areas with higher initial high-tech intensity become more productive as universities grow, and at the intensive margin, establishment level analysis finds a positive relationship for high-tech plants themselves.

Understanding the extent to which there are differential effects by university type can reveal information about the mechanisms through which universities affect local economies. To estimate heterogeneous effects, I include the share of students of different types within 30km of the ward centroid in addition to the core university measure. I find that the high-tech start-ups results are larger in magnitude for universities of higher quality and research intensity, and also for those with a higher share of overseas students.[9] Similar patterns are found in the productivity analysis.

While the core analysis addresses concerns about time invariant unobservables via the inclusion of ward level fixed effects, and demand conditions by controlling for population, concerns regarding endogeneity due to time varying unobservables and feedback effects remain. To address these issues, I do two things. First, in the robustness, I show that results largely survive inclusion of region-year fixed effects - a demanding specification where

[9] This last finding is consistent with evidence from the US that has found that immigrants entering on student visas are more innovative and entrepreneurial (Hunt, 2011).

identification comes from comparing changes over time between local areas controlling for shocks or policy changes within the larger geographical area. Second, I construct an instrument based on historical patterns of overseas student enrolment (Machin and Murphy, 2017) to generate exogenous variation in student numbers. This type of instrument is widely employed in the literature on immigration, and uses prior settlement patterns as a source of identification (Bartik, 1991; Card, 2001*b*). It is interesting to examine the reduced form relationships, and instrument for the number of overseas students in order to analyse their impacts on local economies which might make a useful contribution given the ongoing political debate about their inclusion in the UK's migration targets. As an additional robustness check I use a fitted value of overseas students as an instrument for *total* students. Since I cannot rule out a violation of the exclusion restriction - given that overseas students appear to have a differential impact on local industry compared with UK students - these results are interpreted with caution. The IV estimates are similar (and slightly stronger) when I instrument for the university presence variable with the overseas student instrument.

Overall, these results are supportive of there being a role of universities in generating entrepreneurial activity and growth in high-tech sectors. These effects are particularly strong for higher quality, research intensive universities, and in urban and high-skill areas which we might expect to have higher absorptive capacity, thereby benefitting more from agglomeration economies. Such findings are consistent with the literature that has found that the effects of university research on local economies are small, but higher where universities and local industry have stronger links (see, for example, Kantor and Whalley (2014)). Taken together the results on high-tech start-ups and productivity suggest that the economic effects of universities might be larger in the longer run, as local industrial composition adjusts.

This paper contributes to the literature on university-industry links by shedding light on the extent to which a general measure of university presence is related to local economic outcomes, and how this varies by university quality or type. This is in contrast with most previous work which tends to be focused on university research activity or specific sectors.

Moreover, this paper contributes to a smaller body of research on the economic impact of universities in the UK. The UK provides an interesting context from a policy perspective, being home to a world leading university sector which has grown rapidly in recent years[10]

[10] Over the period 2000-2016, the share of 25-34 year olds with a degree has risen particularly rapidly in the UK, compared to the OECD on average, or its main comparator countries the US, France and Germany, see

and experienced a number of policy changes with respect to university finance and assessment. UK universities account for around a quarter of gross domestic expenditure on R&D, which is high by international standards.[11] Today, assessments of research quality place increasing emphasis on "impact"[12], and policymakers highlight the important role of universities in the new industrial strategy which seeks to improve both the UK's aggregate productivity performance and reduce regional disparities (HMG, 2017). While the UK research base is strong by international standards (Elsevier, 2016), there has been extensive policy focus on improving commercialisation (see for example, Dowling (2015)). Some argue that the career incentives of academics are a key barrier to achieving more economic impact (Willets, 2017), while others recommend more focus on improving business demand for innovation (HOC, 2017).[13] There are differing opinions as to whether the university sector has reached an optimal size, or whether further growth would be economically beneficial to the UK or particular regions. By shedding light on the local economic impact of universities and how this varies by university, sector or type of firm, this paper can help inform this debate in the UK, with relevance also for other advanced economies with mature university sectors.

This paper is organised as follows. Section 2.2 provides a brief overview of findings from the existing literature on the economic impact of universities and sets out how this paper relates to it. Section 2.3 describes the data and some of its key features including some correlations that motivate the paper. Section 2.4 sets out the econometric strategy, and Section 2.5 the results. Section 2.6 provides some concluding comments.

2.2 Relevant Literature

In analysing the relationship between the number of students in a local area and economic outcomes, this paper links to the human capital and growth literature. Human capital has been shown to matter for regional economic outcomes (see for example Gennaioli et al. (2013) and Gennaioli et al. (2014)). There is the direct impact of skilled workers being

OECD Education at a Glance, 2017 (Table A1.2). This increase is highlighted in Corry, Valero and Van Reenen (2011) as contributing to UK productivity growth between the late 1990s and the financial crisis.

[11] In the US, the equivalent share is 13% , for Germany it is 18%, and the OECD average is 17% (OECD MSTI, Percentage of GERD performed by the Higher Education sector, 2016).

[12] The most recent assessment, the REF 2014, was the first to assess impact outside of academia, defined as "an effect on, change or benefit to the economy, society, culture, public policy or services, health, the environment or quality of life, beyond academia". Following review (Stern, 2016), the REF 2021 will give impact increased weight.

[13] Also in development is a new Knowledge Exchange Framework to benchmark universities' performance at knowledge exchange and commercialisation.

on average more productive than unskilled workers, as well as indirect spillover effects of the human capital in cities or regions, as measured in individuals' wages (Moretti, 2004*a*) or firm productivity (Moretti, 2004*b*; Gennaioli et al., 2013). Feng and Valero (2018) show firms closer to universities tend to have higher management scores (Bloom and Van Reenen, 2007) and employ a higher share of graduates which appears to be due to universities increasing the supply and reducing the relative cost of graduates.[14] For university graduates to affect the local economy, at least some would need to remain in the same area post-graduation, working in local firms or starting their own businesses. Data on employment destinations of UK domiciled undergraduate students six months after graduation show that across local enterprise partnerships (LEP), nearly 40% of students on average stay in the same LEP as that in which they studied.[15] It has been established that proximity matters in terms of increasing the probability of locally born young people attending university (e.g. Card (2001*a*)); and indeed in the UK, on average 34.5% of students go to university in the LEP where they grew up.[16] Therefore, in this context it is reasonable to assume that universities increase local human capital in the workforce both by training students from the local area, and by pulling students into a region from elsewhere.

To the extent that the size and composition of universities reflect their research activity, this paper connects to the literature on universities and local innovation spillovers. Such spillovers can occur through formal or informal interactions between university research and businesses, and the innovative activities of staff, students and graduates themselves. To the extent that universities develop human capital in particular in the younger generations, they might be also be expected to be linked to the most creative or ground-breaking innovations (Acemoglu, Akcigit and Celik, 2014). Innovation is not directly measured in this paper, but the reduced form relationship between changes in university size and local economic outcomes such as high-tech start-ups or productivity are likely to reflect changes in innovative activity. The literature on innovation spillovers from university research has been largely based on US data, and stems from Jaffe (1989), who finds evidence of commercial spillovers from university research (to firm patenting or R&D). A number of

[14] This pattern is also highlighted in the US using proximity to land-grant colleges by Bloom, Sadun and Van Reenen (2017).

[15] Data sourced from HEFCE, Geographical Mobility of Students, based on first degree students who studied in higher education in the years 2010-11 to 2014-15 inclusive. This share is highest for London (at 72.7%) and lowest for Oxford (23.1%). Local Enterprise Partnerships are individual or grouped local authority areas which partner with businesses.

[16] This ranges from 65.1% for the North Eastern LEP, down to 14.2% for Thames Valley Berkshire, based on HEFCE data.

subsequent papers provide evidence of localisation (see, for example, Jaffe, Trajtenberg and Henderson (1993), Anselin, Varga and Acs (1997), Belenzon and Schankerman (2013)). Andrews (2017) exploits quasi random allocation of universities to US counties over the period 1839-1954 to estimate their causal impact on patenting. This paper also examines the channels driving these effects, and finds that the largest share of induced patenting came from people who migrated into the university counties, rather than from staff or graduates from the new universities.

Other papers relate university innovation or research activity to local economic outcomes. Hausman (2017) exploits variation induced by the Bayh-Dole Act (1980) which gave US universities property rights to innovations and therefore raised incentives to patent, finding that employment and pay increased in sectors closely tied with university innovative specialisms.[17] Then there are papers that analyse the impacts of research spending by universities. Kantor and Whalley (2014) develop an instrument for university research spending based on endowment values, and find a positive but small effect on labour income in large urban US counties, again with a larger effect for sectors that are technologically closer to nearby universities. Aghion et al. (2009) show that increases in research investments at universities affect growth and patenting in US states. The impact of university research spending on start-ups is analysed by Woodward, Figueiredo and Guimaraes (2006), who find a positive but small effect of science and engineering research spend on high-tech start-ups in the US manufacturing sector in the 1990s.[18] Using the number of university researchers employed as a measure of investment, Andersson, Quiley and Wilhelmsson (2009) study the effects of university expansion in Sweden that occurred in the late 1980s and 1990s, and find that output per worker and patenting has been greater in municipalities where more university researchers are employed, and that the effects are strongly localised.

Studies in the UK tend to be focused on the relationships between scientific research in universities and the extent or location of business research and innovation in specific sectors. Considering the manufacturing sector only, Helmers and Rogers (2015) find positive effects of university research on the patenting of small firms located near to universities (but no impact on large firms), and that the quality of university research

[17] Hausman finds that employment growth is largely driven by firm entry, in particular from multi-unit firm expansions rather than single-unit entrants (though the latter group were more plentiful); and increased exit in incumbent firms, consistent with a process of "creative destruction".

[18] See also Bania, Eberts and Fogarty (1993) and Zucker, Darby and Brewer (1998), who consider the impacts of research spending and the presence of top scientists respectively on start-ups in specific manufacturing sectors in the US.

matters. In a study focused on eight product groups in manufacturing, Abramovsky and Simpson (2011) study whether firms conducting R&D co-locate research activity near to universities, finding positive effects in the pharmaceuticals sector, but less or no evidence of co-location in other sectors.[19]

To date there are fewer papers that consider the general economic impact of universities on their local areas and across sectors. Over and above the human capital and research channels, universities might impact upon local areas through other interactions with business and the community, for example consultancy, sharing of facilities and infrastructure or working with local or regional bodies on regeneration projects.[20] Moreover, university-business interactions might generate innovation that is not picked up via patenting measures, which tend to be a more relevant metric in manufacturing than services. Some papers based on US data take a more general approach than the innovation focused papers discussed previously. In older work, Beeson and Montgomery (1993) find weak evidence that university quality affects the employment rate and the share of high-tech employment in metropolitan areas. A recent study by Liu (2015) examines the impact of land grant colleges in US counties on population density and the manufacturing sector using synthetic controls and event study methods. He finds a positive effect of university designation on population density, no impact on the size of the manufacturing sector, and only long run effects on manufacturing productivity.[21]

A robust association between universities and regional GDP per capita is found by Valero and Van Reenen (2018) using international data. As noted in that paper, the university count measure cannot capture variation in size and quality over time and we might expect economic impact to vary accordingly. Moreover, the analysis is based on a regional panel and cannot rule out endogeneity due to time varying unobservables, nor examine the extent to which results might be driven by particular industrial sectors or types of firm. This paper fills some of the gaps, using granular data on firms and universities which allows for a more detailed analysis, and employing a number of strategies to address endogeneity concerns.

[19] Papers that analyse the effect of university research activity on area or firm level performance include Guerrero, Cunningham and Urbano (2015), who find positive relationships between university teaching, research and entrepreneurial activities (spin-offs) and the productivity of 74 NUTS 3 regions in the UK, with the entrepreneurial activity effects being particularly strong for Russell Group universities; and Harris, Li and Moffat (2011) who find a positive relationship between establishment - university research collaboration and TFP.

[20] For more details of the different types of activity in which UK universities engage, see the Higher Education – Business and Community Interaction Survey HEFCE (2017).

[21] See also Cantoni and Yuchtman (2014) who highlight the role of the medieval universities during the Commercial revolution using historical data on German cities.

2.3 Data

I combine administrative data on UK universities sourced from the Higher Education Statistical Authority (HESA), with data on UK firms, their location, employment and financial performance sourced from the UK's Office for National Statistics (ONS).

2.3.1 University Data

I obtained administrative data on annual enrolments at higher education institutions between the academic years 1994/1995 and 2015/16 from the Higher Education Statistics Authority (HESA). For each institution, the annual number of students (as at 1st December) are broken down by level of study, mode of study (full time or part time – which I use to calculate full time equivalent, FTE, students), gender, subject area, and country of domicile. Institutions are merged with a listing of UK universities from the World Higher Education Database (WHED) (Valero and Van Reenen, 2018) which gives university postcodes and hence allows them to be geocoded. For the purposes of this paper, institutions in Northern Ireland are excluded, as firm level performance data are available for Great Britain only.

Data are provided for the institutions using their names in a given year, and in order to create a panel it is necessary to correct for name changes and mergers.[22] The final sample of institutions is based on their form in the most recent year of data. So, for example, Edinburgh College of Art merged into the University of Edinburgh in 2011/12. The address of the merged institution will be the main address of the University of Edinburgh throughout the panel, and data for these institutions pre-2011/12 are aggregated.

HESA data are collected for higher education institutions, which includes higher education colleges in addition to universities, and there are a number of institutions that enter the data during the period. The university sample used in this paper consists of 136 established and recognised university institutions for which data are available during the entire sample period (Appendix 2.A details the institutions included and excluded from the sample). Institutions that enter the HESA data in the period since the mid 1990s are generally pre-existing institutions gaining recognition in the higher education sector, rather than newly founded institutions on greenfield sites (which was the case with the "plate glass" universities in the 1960s). Such institutions are dropped from the university sample as they would create artificial jumps in the size of the university sector in local

[22] The information required to do this is available at https://www.hesa.ac.uk/support/providers/mergers-changes.

areas.[23]

Data on enrolments by subject group are used in heterogeneity analysis, and in conjunction with information on country of domicile, for the construction of the overseas instrument. Students within 19 JACS subject areas are aggregated into five groups,[24] three of which might be expected to have stronger impacts on local firms: these are STEM and Medicine (and related courses) which are generally associated with university innovation and collaboration with firms, and social science, law and business courses which might be relevant for graduates working in industry or other types of business support that affects local growth (for example, consultancy services or training).[25]

Student enrolments have risen over the study period. Splitting FTE students into UK and overseas (Figure 2.3.1A) shows that there has been a rise for both UK and overseas students, though there was a dip after 2012 for UK students. This has been attributed to demographic decline in the young population and a fall in the number of people studying part time (UUK, 2015). Recent analysis has shown that the rise in university fees in 2012 did not have a large impact on student enrolments (Azmat and Simion, 2018). Splitting total enrolments into undergraduate and postgraduate students shows that again both have risen over the period and that the dip from 2012 is more pronounced for undergraduates (Figure 2.3.1B).[26] In fact, the vast majority of institutions in the sample (128 out of 136) have seen positive average annual growth on an FTE basis during the period (result not shown).

2.3.2 Firm Level Data

ONS micro-data relate to different levels of the firm. The"local unit" is the business site, and the "enterprise" is the overall firm. While these are the same in many cases, they differ for firms that are multi-unit (for example a supermarket chain). Administrative data on employment are available for both of these units, and since this paper examines spatial relationships between firms and universities, the local unit (which I refer to as the establishment) is the relevant unit of analysis.

[23] Enrolments of the institutions entering HESA data over the period represent 1% of total enrolments of the university sample in 2016. To the extent that there are persistent differences for particular areas due to exclusion of such institutions, these will be absorbed by area or establishment level fixed effects in the regressions.

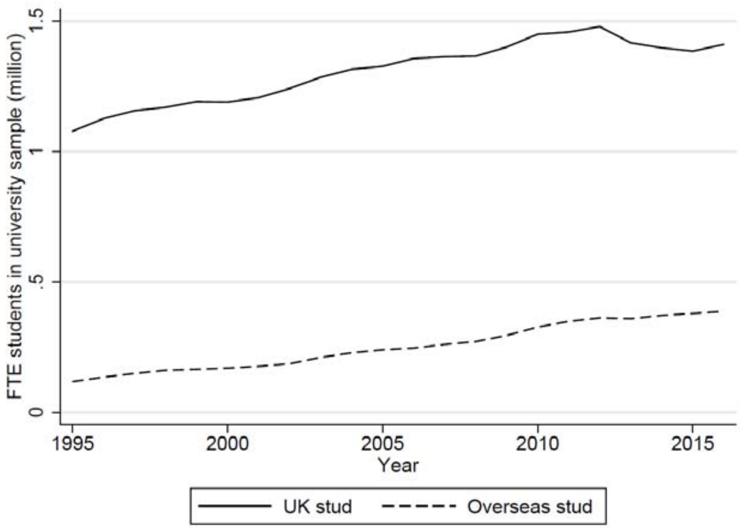
[24] See Appendix 2.A for further details.

[25] Britton et al. (2016) have shown that medicine, economics, law, mathematics and business courses attract significant wage premia, reflecting their economic value.

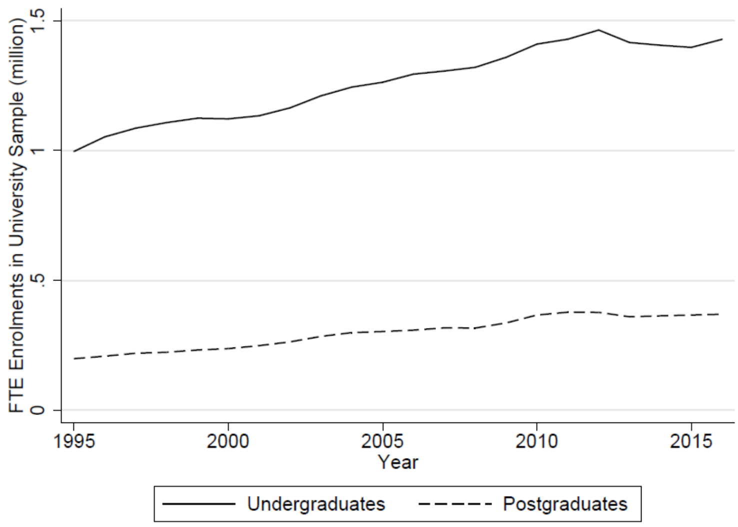
[26] In fact it is "other undergraduate" courses (such as diplomas and foundation courses) that drive this trend, rather than first degrees (UUK, 2015).

Figure 2.3.1: University Enrolments over Time

A: UK and Overseas Students



B: Undergraduate and Postgraduate Students



NOTES: Analysis based on HESA data, university sample refers to 136 established universities observed throughout the period.

Data on the population of establishments, and their employment is based on the Inter - Departmental Business Register (IDBR), a live record of VAT or PAYE registered businesses which is available over the period 1997-2016. These data are accessed via the Business Structure Database (BSD) which provides an annual snapshot of the register.[27] Using the ONS Postcode Directory (2015), establishment postcodes are mapped to 2015 electoral wards, of which there are 8,734 in the main sample.[28] The count of establishments and

[27] Office for National Statistics. (2017). Business Structure Database, 1997-2017: Secure Access. [data collection]. 9th Edition. UK Data Service. SN: 6697, http://doi.org/10.5255/UKDA-SN-6697-9

[28] There are 9,198 electoral wards across the UK in the ONSPD 2015 (variable *osward*). The analysis in this

their employment are then aggregated to the ward level in each year. Information on establishment birth and death dates are used to calculate entrants and exits, and details on whether or not the establishment is part of a single-unit or multi-unit enterprise are used to identify start-ups which I define as single-unit entrants. Industry codes are also used to allocate establishments to aggregate sectors. All sectors (including the public sector) are included in the initial analysis, but the main focus is on the high-tech sectors which are mapped across manufacturing and services (see below).

Financial data are available for a sample of firms in the IDBR from the Annual Business Survey (ABS), which covers the production, construction, distribution and service industries, and represents approximately two thirds of the UK economy. The ABS sample consists of the population of larger businesses (defined based on employment), and a random sample of smaller businesses. I access these data using the newly available "ARDx",[29] which combines and harmonises variables in the ABS and its predecessor survey over the period 1998-2015.

The key performance measure used in this analysis is Gross Value Added (GVA) per worker, in basic prices and deflated using ONS sectoral deflators. GVA is available for the "reporting unit" of the firm. The reporting unit tends to be the same as the enterprise in most cases, but might differ in large companies with different reporting divisions. As is standard in the literature, I apportion reporting unit financial variables to the establishment level using the its share in total reporting unit employment (see for example, Gibbons et al. (2017)), a method which implicitly assumes that productivity is equal in all parts of the firm. I aggregate GVA and employment to the ward level based on this sample, and then calculate GVA/employment.[30] I also obtain data on capital investment, wages, turnover, output and profitability[31] and capital stock estimates based on the ARDx methodology.[32]

Across both the BSD and ARDx datasets, high-tech sectors are allocated according to classifications given by NESTA (Bakhshi et al., 2015) which build on Eurostat methodology (based on R&D and knowledge intensity), but use also information of the STEM intensity

paper excludes Northern Ireland (462 wards), the Isle of Man (1) and the Channel Islands (1), leaving 8,734.

[29] Office for National Statistics. Virtual Microdata Laboratory (VML), University of the West of England, Bristol. (2017). Annual Respondents Database X, 1998-2014: Secure Access. [data collection]. 4th Edition. Office for National Statistics, [original data producer(s)]. UK Data Service. SN: 7989, http://doi.org/10.5255/UKDA-SN-7989-4

[30] Normalising by employment helps to avoid issues regarding the representativeness of ward level aggregates based on the establishments covered by the ABS sample (either because they are reporting units themselves, or because they are part of multi-establishment reporting units that have financial data apportioned to them).

[31] Profitability is normalised by turnover to calculate a profit margin.

[32] These estimates, sourced from the ARDx, are still in development. Future work will use the updated methodology when it becomes available, and conduct more in depth analysis of TFP.

of occupations within sectors. Further details of data cleaning and assumptions are in the Data Appendix 2.A.

2.3.3 Measures of University Presence

The main measure of university presence is enrolments at universities located within 30km of the centroid of a ward. I also examine sensitivity of the main results by using different radii (10km and 50km). This range is consistent with related UK literature, for example Abramovsky and Simpson (2011). Given that the analysis is in a panel set-up, this is the most appropriate time varying measure of university presence over the time period analysed. University size is used as a proxy for university activity, since in general, a larger university can potentially have a higher impact through graduates entering the labour market, and allowing for differing student-staff ratios[33], more students should imply more staff and resource for research or other activities relevant for local industry.

These measures are constructed using Stata's "geonear"[34] function, which calculates geodetic distances between two points based on their co-ordinates (the length of the shortest curve between two points along the surface of a mathematical model of the Earth). This allows the identification of the nearest university for each ward[35], and also all the universities within a given radius. By merging in enrolments data, it is therefore possible to calculate the number of students currently studying within a given radius of the ward or establishment in a given year.

Figure 2.3.2 summarises the main university presence measure. Panel A gives a snapshot of the data in the most recent year (2016), which shows that there is variation across Great Britain, with a concentration of students around London and some other metropolitan areas. Panel B shows a long difference from 1995-2016, and reveals that there is variation in the growth of enrolments, and that growth has not necessarily been concentrated in economically more successful areas (for example, there is a large increase in Cornwall which is driven by the expansion of the University of Falmouth). There are 1,484 wards (17% of the total sample) that do not have any university presence according to my definition during the sample period.

In order to capture heterogeneity, I calculate the share of students of different types

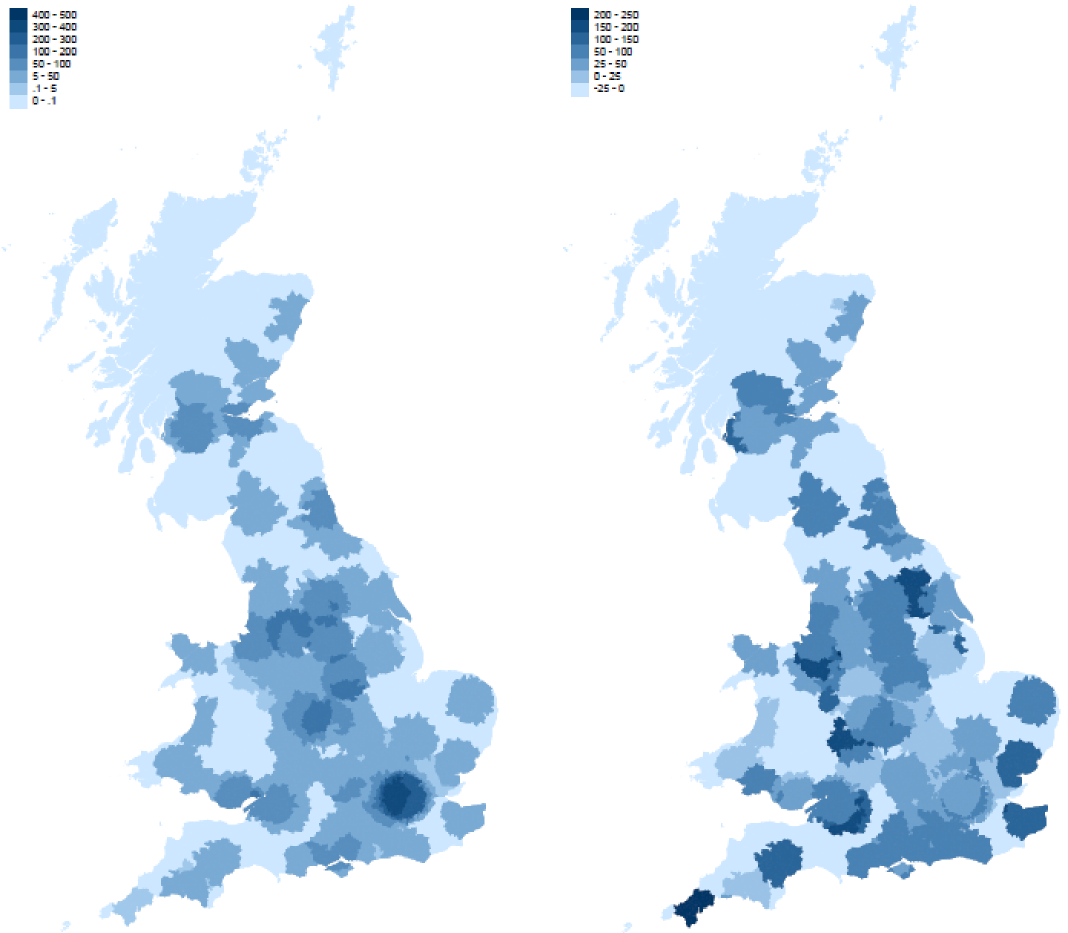
[33] These vary between around 10:1 and 20:1 in the UK (https://www.thecompleteuniversityguide.co.uk/league-tables/rankings?o=Student-Staff+Ratio& y=2016), with lower ratios at the more prestigious universities.

[34] http://fmwww.bc.edu/repec/bocode/g/geonear.html

[35] Latitude and longitude for each postcode are given in the ONSPD. The co-ordinates of the ward centroid is calculated as the average latitude and longitude of postcodes within a ward.

Figure 2.3.2: Maps of Ward Level Enrolments Within 30km

A. Enrolments within 30km (1000s), 2016 **B. Enrolments within 30km, % change 1995-2016**



NOTES: Analysis based on HESA data, university sample refers to 136 established universities observed throughout the period.

within a 30km radius. Research intensity is proxied by the share of postgraduate students, and specialisms reflected by the share of postgraduates enrolled in scientific (STEM or medical sciences) or business related degrees (business, law or social science). As a simple measure of quality, I calculate the share of students enrolled at the higher ranking Russell Group[36] universities, which have higher resource and performance compared to other universities (McCormack, Propper and Smith, 2013).[37] Since these measures are based on

[36] There are 24 universities in the Russell Group, which are the group of research intensive institutions collectively responsible for over two thirds of world leading research produced in UK universities (https://russellgroup.ac.uk/about/). Of these, 23 are included in my sample: Queen's University Belfast is excluded because it is in Northern Ireland. In 2015/16 Russell Group universities generated nearly 50% of the total IP income generated by UK universities.

[37] Moreover, Russell Group universities also see themselves competing in national and international markets for staff and students – a feature that has been found to be correlated with university quality (Aghion et al., 2010), compared to newer universities that focus more on local markets (McCormack, Propper and Smith, 2013).

student numbers, they vary over time and can be calculated for the entire sample period.[38]

2.3.4 Descriptive Statistics

Table 2.3.1 summarises the data used in the ward level analysis based on the BSD (Panel A) and ARDx (Panel B). The BSD ward sample contains 165,946 ward-year observations, relating to 8,734 wards. Since I lag the university enrolments three years, and the university data are available from 1995, the BSD analysis sample covers the period 1998-2016. The average ward over the sample period has 275 establishments, employment of 2,865, and the average establishment has around 9 employees. There are 31 entrants, on average, in a given year, of which 26 are single-unit establishments. There are also 26 exits in the average ward – year. There are 37 establishments in the high-tech sectors, representing 13% of total establishments, and together they employ 297. There are 5 single-unit entrants in these sectors, which I refer to as high-tech start-ups, the outcome variable of focus in the ward level analysis which uses BSD data. Overall, 60% of wards can be considered urban.

The average numbers of students, universities and population within 30km from the centroid of the ward are also given. I focus on the FTE measure of students (full time students plus half of part time students), of which there are on average just over 54,000 within 30km of the average ward during the sample period. There are 5 universities within 30km of the average ward, and the nearest university is 18km away. The key area level control used in the analysis is population within the same radius as the enrolments measure, based on census data (for more detail see Data Appendix 2.A). The average population within 30km is just over 2 million.

I also provide summary statistics of the key measures of university heterogeneity: over the period, on average 18% of the students within 30km of the average ward are enrolled at Russell Group universities and 15% are postgraduate. Of total students, on average 5% are studying STEM and medicine related subjects at the postgraduate level, and a similar proportion are studying social science and business courses. 12% of students are domiciled overseas.

The key variables used in the productivity analysis based on the ARDx sample are

[38] Other available measures of quality include Research Excellence Framework (REF) scores (and their predecessor the RAE) which are only available three times over the sample period (2001, 2008 and 2014) and have changed in methodology over time, or university rankings which tend to be published every year (the Complete University Guide (CUG), for example, is available annually from 2008). The share of students in Russell Group universities is a more straightforward way to account for quality in this set-up rather than trying to combine individual university rankings with the enrolments data over time, but measures extracted from the REF and CUG are used in the cross-sectional analysis.

Table 2.3.1: Descriptive Statistics

	Mean	SD
A: BSD wards sample (N=165,946 and 8,734 wards)		
Establishments	275	420
Employment	2,865	5,910
Employment per establishment	9	7
Entrants	31	91
Single-unit entrants	26	86
Exits	26	108
Establishments in high-tech sectors	37	59
Employment in high-tech sectors	297	796
Single-unit entrants in high-tech sectors	5	22
Ward share of urban postcodes	0.60	0.50
Students within 30km (FTE)	54,436	76,535
Students within 30km (FT+PT)	63,461	89,902
Universities within 30km	5	9
Km to nearest university	18	20
Population within 30km	2,092,577	2,272,322
% Russell Group students	17.7	22.2
% Postgraduate students	14.9	8.7
% Postgraduate STEM, med. students	5.1	4.1
% Postgraduate soc sci, bus. students	4.8	3.0
% Overseas students	12.0	8.0
B: ARDx wards sample (N=139,891 and 8,726 wards)		
GVA per worker	40,985	70,567
Capital per worker	33,187	75,515
Ward share of high-tech establishments (%)	7	6
Ward share of urban postcodes	0.65	0.45
Students within 30km (FTE)	54,202	75,619
Students within 30km (FT+PT)	63,483	89,325
Universities within 30km	5	9
Km to nearest university	18	20
Population within 30km	2,105,692	2,261,299

NOTES: Panel A summarises the BSD ward sample and relates to the years 1998-2016 (1997 is dropped from the sample as there are no 3 year lagged students in the HESA data which start at 1995). Panel B summarises the ward sample based on ARDx data and relates to the year 1998-2014 (2015 is dropped because capital stock is not available for that year). Observations with missing employment or financial data which reappear later in the sample are interpolated for the purposes of calculating ward level variables. "High-tech" sectors are allocated according to NESTA(2015). The university measures are based on distances of universities from the centroid of the ward.

summarised in Panel B. This consists of 139,891 ward-year observations, relating to 8,726 wards where financial data on reporting units and their corresponding local units were available – nearly all the wards in the BSD sample. The average ward has GVA per worker of £40,985 during the sample period (in 2013 prices). The core sample is for the years 1998-2014, as those are the years where capital stock estimates are available. Average capital per worker is £33,187 over the period. The average share of high-tech employment within a ward is 7% in this sample. The urban share, university presence variables and population are similar to the BSD sample.

An analogue table for the establishment level analysis is given in the Appendix (Table 2.B.1), based on unbalanced panels of live establishments which are observed repeatedly over the sample period. These descriptives give some more detail on the types of establishment in the data: the average establishment in the BSD sample is small, employing 11, and in fact only 3% of the sample is classified as a large establishment (employees greater than or equal to 50 in its first observation in the sample period). 38% of the sample are classified as "young" (under 5 years since birth), 14% operate in the high-tech sectors, and nearly 50% are part of multi-unit enterprises. A higher share of this sample is urban (72%), and accordingly, the average establishment has nearly 80,000 students within 30km, and a population of nearly 3 million within that radius. Establishments in the ARDx sample are slightly larger on average due to survey design (and these also tend to be more urban). The average establishment has 41 employees, and this sample has a higher fraction of large establishments (16% versus 3% in the BSD sample). The university presence measure is similar to the BSD sample.

2.3.5 Basic Correlations

Table 2.3.2 reports the cross sectional univariate correlations between ward level, establishments, employment, employment per establishment, and GVA per worker against different measures of university presence using the data in the latest available year only (2016 in the BSD, 2015 in the ARDx). The natural log of outcomes and university presence variables are taken (+1 to retain zeroes in the sample). Each cell represents a different regression of the dependent variable (column) on a university measure (row), with no other controls, and robust standard errors are in parentheses. Columns (1) - (3) give the results for the number of establishments and employment based on BSD data. These correlations are all significant at the 1% level and of the expected sign: positive for the measures based on enrolments and numbers of universities, and negative for the distance measure in row J, i.e. ward employment and establishments are lower the further away the closest university is from the ward. Rows G to I regress employment and establishments on students normalised by population. The relationships remain positive and significant relationships but are smaller in magnitude. The coefficients are broadly similar for the

10km, 30km and 50km radius. The correlations in column (3), for average employment, are smaller than the coefficients for total employment, suggesting that much of the increased employment associated with universities could be related to entry of new, smaller establishments.

Table 2.3.2: Basic Correlations

		(1)	(2)	(3)	(4)
		Dependent variable:			
University Presence measure:		ln(estab.)	ln(emp)	ln(ave emp)	ln(gva/emp)
A	ln(students, 10km)	0.0517***	0.0665***	0.0130***	0.0105***
		(0.0017)	(0.0023)	(0.0011)	(0.0015)
B	ln(students, 30km)	0.0450***	0.0567***	0.0101***	0.0128***
		(0.0019)	(0.0025)	(0.0012)	(0.0021)
C	ln(students, 50km)	0.0708***	0.0822***	0.00952***	0.0190***
		(0.0042)	(0.0053)	(0.0023)	(0.0035)
D	ln(unis, 10km)	0.470***	0.541***	0.0628***	0.0977***
		(0.0106)	(0.0156)	(0.0085)	(0.0105)
E	ln(unis, 30km)	0.336***	0.356***	0.0171***	0.0833***
		(0.0076)	(0.0107)	(0.0055)	(0.0082)
F	ln(unis, 50km)	0.311***	0.316***	0.0029	0.0792***
		(0.0081)	(0.0112)	(0.0056)	(0.0085)
G	% students/population, 10km	0.0304***	0.0464***	0.0142***	0.00730***
		(0.0030)	(0.0038)	(0.0016)	(0.0020)
H	% students/population, 30km	0.0349***	0.0495***	0.0130***	0.0114**
		(0.0057)	(0.0076)	(0.0033)	(0.0052)
I	% students/population, 50km	0.0405***	0.0598***	0.0173***	0.0154*
		(0.0099)	(0.0132)	(0.0058)	(0.0089)
J	ln(distance to closest uni)	-0.303***	-0.405***	-0.0899***	-0.0598***
		(0.0106)	(0.0136)	(0.0062)	(0.0089)
	Observations	8,734	8,734	8,734	8,480

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Each row is a separate regression of the dependent variable on different measures of university presence in turn (rows A-J). Note that students and population measures are lagged three years for consistency with main analysis. Columns (1) to (3) are based on BSD data, and cross sectional regressions for 2016 only, N=8,734 ward level observations. Column (4) is based on ARDx data, and cross sectional regressions for 2015, N=8480 ward level observations for all regressions. Regressions contain no additional controls. Robust standard errors in parentheses.

Column (4) reports the cross-sectional relationships between different measures of university presence and GVA per worker. Again, Rows A-F show that there are positive and significant relationships between student and university numbers within all radius measures. Once students are normalised by population, the GVA per worker result remains positive but becomes smaller and less significant at larger radius. Distance to closest university is negatively and significantly correlated with labour productivity.[39]

[39] This is consistent with the result based on international data in Feng and Valero (2018).

Some other dimensions of these correlations are explored for descriptive purposes in the Appendix. Table 2.B.2 looks at how the relationship between the distance to university measure and number of establishments, employment and new entrants differ for closest universities of higher quality (as measured by Russell Group status or REF scores), showing that wards with a closest university of higher research quality tend to have higher employment, establishments and new entrants, and distance matters more in these cases. The same pattern is found when the dependent variable is single-unit establishments in the high-tech sectors only (result not shown).[40] These cross-sectional relationships accord with the notion that clusters of economic activity surround universities in the UK and motivate the analysis that follows.

2.4 Empirical Strategy

2.4.1 Ward Level Panel Regressions

The analysis seeks to estimate how the size of the university sector affects local economic outcomes. The general estimating equation is:

$$ln(Y_{r,t}) = \alpha_1 ln(UP_{r,t-3}) + \alpha_2 ln(Pop_{r,t-3}) + \eta_r + \tau_t + \varepsilon_{r,t} \qquad (2.4.1)$$

Where $Y_{r,t}$ is the outcome variable analysed for the ward r and time t. The key outcome variables at the ward level are the number of establishments, employment and start-ups in a given year (the natural log of 1 plus these values is used so that zeroes are retained in the analysis). Based on the population of establishments in the BSD, these can also be split into sector groupings, in particular, those in the high-tech sectors which are across manufacturing and services. In the productivity analysis the outcome is labour productivity (GVA/worker), and capital per worker is also controlled for.

The measure of university presence, $UP_{r,t-3}$, is the number of students enrolled within a given radius of the ward (30km in the core specifications, but I also estimate effects for 10km and 50km in the robustness), plus one so that areas with no universities are retained. The university variable is lagged three years as most undergraduate university programmes in the UK last for three years (and Masters programmes for less), so it is reasonable to assume that the majority of students enrolled in a given year will have

[40] There were similar results using the Complete University Guide research quality ratings (which themselves are based on REF scores). There were no systematic relationships in the cross section for other measures in the Complete University Guide, such as overall university rank or student satisfaction.

graduated three years later. In addition, lagging this measure allows us to eliminate the effects of a contemporaneous demand shock that might have an impact on both firm outcomes and university enrolments. I experiment with alternative lags in the robustness and find that the three-year lag is a reasonable assumption. The coefficient of interest therefore is α_1 which, given the log-log specification provides an estimate of the elasticity of the outcome variable with respect to student enrolments.

The main control is population, scaled consistently with the university variable (i.e. population within wards that are within 30km of the centroid of economic unit), which should reflect other time varying factors that may be related to economic growth and also the growth student enrolments in a particular area, such as demand shocks. Including population also should capture the direct demand effects of universities themselves – i.e. the effects of universities on surrounding firms via staff and students consuming goods and services. In other words, the university effect, controlling for population, should be driven by human capital, innovation or other effects of universities on local areas.

The cross-sectional relationships between universities and economic outcomes are likely to be subject to omitted variable bias as there are a number of unobservables that might be correlated with both the size of the university sector in an area and firm performance. Therefore, the main estimating equation controls for ward specific (η_r) unobservables in a fixed effects framework. All regressions contain year specific (τ_t) fixed effects to control for country-wide shocks. Finally, $\varepsilon_{r,t}$ is an error term which is clustered at the ward level (results are robust to alternative assumptions).

We might expect α_1 to be positive in general across outcomes such as number of establishments, employment and productivity, based on previous literature that has linked university research activity to local innovation and growth. But universities might also have negative effects on some or all of these outcomes if they and their related activities crowd out local industry. Universities themselves are large employers, and create additional demand for housing, land and other services which, with fixed supply, can lead to rising factor costs such as wages or rent. Such forces could lead to existing establishments exiting, moving away, employing fewer workers, or making fewer productivity enhancing investments.[41] Moreover, if universities stimulate increased start-up activity this will add to local competitive pressure (possibly in product as well as factor markets) and less

[41] In the UK there are concerns that restrictions on housing supply and inadequate infrastructure could hold back the growth of the "Cambridge-Milton-Keynes-Oxford Corridor" (National Infrastructure Commission, 2017).

productive incumbent firms might be expected to suffer, as found by Hausman (2017). In addition, areas with higher numbers of start-ups might also have depressed measured productivity on average due to lower mark-ups (Foster, Haltiwanger and Syverson, 2008), at least in the short run. For all these reasons, we might also expect differential effects for different types of firm or area.

I analyse heterogeneity by university type to gain a better understanding of the mechanism through which universities affect their local economies. In these specifications, I add a term representing the share of students of a particular type within the same radius as overall students. Based on the existence of clusters such as Silicon Valley or Cambridge, and academic evidence[42] we might expect institutions of higher quality or research intensity to have a larger impact on their local areas, but it is also possible that their impacts are felt at a wider spatial scale – for example if higher quality graduates are more mobile, or if world leading research is disseminated further afield. In contrast, lower quality universities might be more focused on impact in their local areas. Evidence from graduate wages also suggests that that there are large differences in the extent to which different universities and courses provide economic value to their students (Britton et al., 2016), and we might expect similar patterns with respect to industry.

While I use a number of measures to get at heterogeneity in focus and quality of the institutions, these data do not allow me to disentangle the mechanisms at work or capture heterogeneity in terms of engagement with local industry or policymakers. On this basis, and in common with Valero and Van Reenen (2018), I seek to estimate a general impact of universities on local areas, in contrast with papers that look specifically at research activity of universities (for example Kantor and Whalley (2014), Hausman (2017) or Aghion et al. (2009)). I also examine heterogeneity by area type, splitting the sample into rural and urban wards, those with higher initial human capital, and dropping well known high-tech clusters (London, Cambridge and Oxford).

Concerns remain that changes in university enrolments are correlated with time varying unobservables in an area. One example could be that a local government begins a programme of development which makes the area more attractive to university students and also businesses, for example infrastructure investments or urban regeneration projects. In such cases, an observed positive relationship between universities and entry of new

[42] For example, Abramovsky and Simpson (2011) show that research quality affects the location of firm R&D in the UK. Helmers and Rogers (2015) find that university quality affects the patenting of small firms (but has no effect on large firms).

businesses might not be driven by the university sector at all. To address these concerns, in the robustness I add region-year fixed effects and show that results are largely robust to these.[43] Second, I develop an instrumental variables strategy based on overseas students.

2.4.2 Overseas Students Instrument

The purpose of this analysis is to try to generate a source of variation in student enrolments that is exogenous to local conditions. I focus on changes in overseas students, developing a "shift-share" type instrument to generate predicted values of overseas students at each university over time (Machin and Murphy, 2017). The idea is that students originally from a particular country are more likely to attend universities and study subjects in common with previous students from that country. The instrumental variable used to predict the stock of overseas students at each university u in each year t is:

$$\widehat{OS_{ut}} = \sum_{s=1}^{S} \sum_{c=1}^{C} OS_{cst} \times \frac{OS_{ucs0}}{OS_{cs0}} \tag{2.4.2}$$

Where s represents the subject area, and c country of domicile. I use information on specific country of domicile[44] and subject areas, split broadly into six groups (STEM, medicine and related subjects, social sciences, humanities, arts and combined courses).[45] For each university u, its share of total students from a particular country c into a subject area s (in the base period $t = 0$, academic years 1994/5 to 1996/7) is applied to the national enrolments of students from that country and subject in subsequent years. The overseas instrument in a given year is then the sum of predicted enrolments across subjects and non-UK countries of domicile for each university. Undergraduates and postgraduates are accounted for separately. In robustness, I also calculate an instrument at the more aggregate level for EU and non-EU students and where all subjects are aggregated.[46]

A key assumption underlying this IV strategy is the exogeneity of national inflow rates

[43] I also experiment with controlling for more granular area-year fixed effects (for example at the local authority level) which have more of an impact on the coefficient. I exclude these from my main analysis as they are likely to be highly co-linear with the changes in enrolments within a 30km radius of a ward (which will be positively correlated with the changes in other wards nearby and therefore wider geographical areas).

[44] Taking 82 countries where the number of students over the entire period exceeded 10,000, and grouping remaining countries into "other".

[45] For more detail of the specific subject areas included within these categories see Appendix 2.A.

[46] The advantage of the first instrument is that it allows for specific subject-country of domicile relationships at different universities and therefore might be expected to generate more accurate fitted values for overseas students. However, this method might fail to capture country-subject-university relationships that became more important after the initial period. For example, as shown in Machin and Murphy (2017), following policy changes in China, enrolments of Chinese students in business and economics courses in the UK increased rapidly after 1998/99. Therefore there second instrument, which picks up on the general international nature of the student body across subjects, is a useful check.

from each source country to local economic conditions. The other key assumption is the exogeneity of the initial shares of students at particular universities, which might not hold where demand shocks are serially correlated (see for example, Jaeger, Ruist and Stuhler (2018)) and can lead to a violation of the exclusion restriction. In this setting, the exclusion restriction also requires that overseas students impact on local firms only via their impact on total enrolments. There might be reason to doubt this should overseas students have a differential impact on firms – for example if the higher fee income associated with overseas students subsidises more research activity, or if overseas students are more or less likely to become local entrepreneurs. Given these doubts, I highlight the reduced form and IV estimates of the impact of overseas students. As an additional robustness check of the main high-tech start-ups result, I also instrument for total students using the predicted overseas students. This is appropriate since during most of the period analysed, UK universities faced caps on domestic student enrolments, and as Machin and Murphy (2017) show, international students did not "crowd-out" domestic students (or home students defined as domestic and EU students who have been of the same fee paying status).[47]

2.4.3 Establishment Level Analysis

Ward level analysis captures effects of universities operating at the extensive and intensive margin, reflecting the impacts of establishment entry and exit, and also changes in the performance of existing firms. This is complemented by analysis at the establishment level which provides more of an insight at the intensive margin. Here I analyse how changes in university presence affect establishment size and productivity, and whether there is any evidence of heterogeneity in effects by firm type. The establishment level regression takes the form:

$$ln(Y_{ij,t}) = \beta_1 ln(UP_{ij,t-3}) + \beta_2 ln(Pop_{ij,t-3}) + \eta_i + \gamma_{j,t} + v_{ij,t} \tag{2.4.3}$$

The key outcomes Y for establishment i, in sector j at time t in this analysis are

[47] I explored other potential instrumental variables strategies based on changes in the policy environment. In recent years there have been a number of policy changes that might affect university enrolments differentially for different universities, in particular increases in university fees (in 2006 and 2012) and the lifting of student caps (over the period 2012-2015). However, analysis of the impacts of fees on student participation has found very small effects (Azmat and Simion, 2018), and the lifting of student caps occurred too late in the sample period for analysis in this paper, given the three year lag structure I employ between enrolments and outcomes. Exploring instruments based on these policy changes is left for future work when additional years of data become available.

employment and labour productivity. The university presence and population variables are now calculated based on the postcode of the establishment. Establishment level fixed effects (η_i), together with sector-year fixed effects ($\gamma_{j,t}$) are controlled for. Again, the error term $v_{ij,t}$ is clustered at the ward level to allow for serial correlation between establishments in the same local areas over time. In this analysis, establishments are considered to be local unit-postcode pairs, so that we do not capture changes in university presence resulting from relocation. Therefore, each establishment is uniquely located within a ward r (subscript not included above for ease of notation).

2.5 Results

2.5.1 Universities, Number of Establishments and Employment

I begin with panel regressions of ward level establishments and employment across all sectors on the core university measure: enrolments of FTE students within 30km (Table 2.5.1). Here, all regressions contain year and ward fixed effects, and control for population within the same radius, with standard errors clustered at the ward level. Column (1) shows that the correlation that we saw in the cross section between the number of establishments and students within 30km (Table 2.3.2, row B, column (1)) survives in a panel set-up: the coefficient of 0.0539 is significant at the 1% level. Since the number of establishments is affected by both entry and exit, column (2) and (3) examine the effects of universities on each of these outcomes. While both entry and exit appear to increase as universities grow, the effect for entrants is more than double that for exits (at 0.158 compared to 0.0629). Indeed, the share of entrants to total establishments - or birth rate - increases as universities grow though the effect is small. The coefficient in column (4) implies that a 1% rise in students within 30km leads to a 0.009 percentage point increase in the birth rate. Meanwhile, the effects of universities on total employment are positive and insignificant (column (5)) and actually negative for employment per establishment (column (6)). This could be a composition effect due to the increased share of entrants that tend to be smaller than incumbents. But could also be due to changes at the intensive margin, i.e. negative employment effects for incumbent firms. The establishment level analysis in Section 2.5.3 returns to this question.[48] In further analysis I also run these regressions in a simple

[48] The coefficients on population are also informative, suggesting that establishment entry is higher in wards surrounded by a higher population, and exit is lower. While employment is also higher in more populous regions, the average employment is lower since the effect on entrants dominates. The case where population works in the opposite direction to the university effect is with respect to exits. Excluding population altogether,

long difference form with one observation per ward (taking the natural log of the 18 year difference in the variables, and dividing by 18 so that this difference is annualised) and find the results are similar.[49] In additional results (not reported here), I find that growth in the university presence measure does not have a significant effect on ward population suggesting that their impacts on this margin (university expansion) are not merely due to bringing more people into an area.[50]

Table 2.5.1: Universities, Number of Establishments and Employment, Ward Level Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ln(estab.)	ln(entrants)	ln(exits)	birth rate	ln(emp)	ln(ave emp)
L3 ln(students, 30km)	0.0539***	0.158***	0.0629***	0.941***	0.0247	-0.0229*
	(0.0094)	(0.0144)	(0.0138)	(0.1230)	(0.0159)	(0.0119)
L3 ln(pop., 30km)	1.035***	1.924***	-0.374***	12.35***	0.550***	-0.423***
	(0.0555)	(0.0897)	(0.0836)	(0.8080)	(0.0883)	(0.0723)
Observations	165,946	165,946	165,946	165,946	165,946	165,946
Clusters	8,734	8,734	8,734	8,734	8,734	8,734

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2016. All regressions contain ward and year fixed effects. Standard errors clustered at the ward level in parentheses. Birth rate = entrants/establishments*100.

2.5.2 Universities and Start-Ups

The analysis in Table 2.5.1 suggests that the impact of universities on their surrounding areas, at least defined using a radius of 30km, is mainly at the extensive margin, through stimulating entry.

Entrants can take two forms: they could be part of multi-establishment or multinational enterprises that are newly opened at a particular location – or they could be new businesses set up by an entrepreneur. The latter is commonly thought of as a start-up. In this section, I explore which types of entrant are driving the results. In addition, I explore the extent to which universities to have differential effects on start-ups in different

the coefficients on plants, entrants and employment are slightly more positive, suggesting that in general, students move into growing areas.

[49] The only outcome where there is a difference is the exits result, where the result comparing snapshots of exits and lagged university presence in 2016 and 1998 suggests a negative relationship. Given that exits are a "flow", the core panel estimates contain more information on their relationship with university growth.

[50] Other studies considering the more discrete event of new university opening do find that universities lead to increased population density, see for example Andrews (2017) or Andersson, Quiley and Wilhelmsson (2009).

sectors. The results of this exercise are in Table 2.5.2, where each cell represents a different regression.

Column (1) reproduces the total entrants result (Panel A) and then proceeds to include only single-unit entrants in the dependent variable (Panel B), and multi-unit entrants (Panel C). This analysis shows that the effect of universities is largely driven by the single-establishment entrants, though there is a smaller positive and significant effect on multi-unit entrants overall. The regression in column (1), Panel B is depicted in Figure 2.5.1A. Dropping wards containing the 10 highest growth universities over the period actually strengthens the result, but all data are retained in the core regressions.[51]

I then include entrants in particular sector groupings in the dependent variables (columns (2) to (7)), and the share of employment of these groupings are given in the bottom row of the table, based on 2016 data. Focusing on Panel B, single-unit entrants, which appear to drive the overall results in most sectors, there are positive and significant coefficients on universities across all broad sectors, apart from manufacturing. Some of these are intuitive: the result for retail, hotels and food might be expected to the extent that university students and staff might consume such services differentially to the general population (which is controlled for in the regressions). In addition, the effect for the education sector (which excludes the HE sector itself) is intuitive as a larger university sector can be expected to increase demand for other education services.[52] Similarly, finance, business and real estate contains R&D activities; and the positive effect for "other" services appears to be driven by community recreation and health services; both of which might be expected to expand as the university sector grows. The larger coefficient in column (5) is more surprising and on closer inspection this is driven by mainly by construction activity (which has a coefficient of over 0.15). Effects for multi-unit entrants are significant only in the education and "other services" sectors (driven by community, personal and social services).

[51] Given that these plots are conditional on ward and year fixed effects, and lagged population growth within 30km, the x and y axis variables are residualised, and variation will come from changes within wards over time. The universities experiencing the highest growth over the sample period will therefore contribute to the outlier bin.

[52] In addition to standard schools and colleges (private and public sector), this sector also includes tutor and other educational support services.

Table 2.5.2: Universities and Establishment Entry, by Sector and Type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sectors:	All	Manu	Retail, food, hotels	Finance, business, real estate	Agric, utilities, constr.	Education	Other	High-Tech	Non High-Tech
A: Dep var is ln(entrants)									
L3 ln(students, 30km)	0.158***	0.00398	0.0954***	0.0901***	0.179***	0.0608***	0.108***	0.0985***	0.158***
	(0.0144)	(0.0153)	(0.0161)	(0.0175)	(0.0176)	(0.0103)	(0.0180)	(0.0185)	(0.0145)
B: Dep var is ln(single-unit entrants)									
L3 ln(students, 30km)	0.159***	0.00499	0.0948***	0.0917***	0.190***	0.0293***	0.105***	0.0882***	0.160***
	(0.0153)	(0.0148)	(0.0166)	(0.0182)	(0.0176)	(0.0084)	(0.0182)	(0.0185)	(0.0154)
C: Dep var is ln(multi-unit entrants)									
L3 ln(students, 30km)	0.0553***	-0.00224	0.0152	0.014	0.0161	0.0378***	0.0279**	0.00687	0.0519***
	(0.0164)	(0.0073)	(0.0121)	(0.0135)	(0.0118)	(0.0066)	(0.0126)	(0.0106)	(0.0160)
Observations		165,946	165,946	165,946	165,946	165,946	165,946	165,946	165,946
Clusters		8,734	8,734	8,734	8,734	8,734	8,734	8,734	8,734
Sector share in employment		9%	23%	25%	7%	7%	29%	10%	90%

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2016. All regressions contain ward and year fixed effects. Standard errors clustered at the ward level in parentheses. In panels A-C, each cell represents a different regression. Sectors are defined according to SIC2003 sections which are grouped as follows: "Manu" is manufacturing (D), "Retail, food, hotels" refer to sections G and H, "finance, business, real estate" refers to sections J and K; "Agric., utilities, constr." refers to sections A, B, C, E, F; "Education" is section M excluding the university sector itself; and "Other Services" are all other services (including public administration): I, L, N and Q. High-tech sectors as defined by NESTA and mapped to SIC2003. The share in total employment (2016) is calculated as the sum of employment by sector grouping, across 8734 wards in 2016, and then divided by total employment across sectors (excluding the higher education sector).

While the impacts of universities on establishment entry across sectors are of interest, a key hypothesis tested in this paper is whether universities have an effect on start-ups in the high-tech sectors (as allocated across manufacturing and services) and these results are reported in column (8). Panel B shows that there is a positive and significant effect of university growth on high-tech start-ups, and this regression is depicted in Figure 2.5.1B. The effect for non high-tech start-ups is also positive and significant (driven largely by the construction sector).

The magnitudes of these average effects are rather small, and this is consistent with findings elsewhere in the literature.[53] The coefficient of 0.0882 for single-unit entrants in the high-tech sectors implies that a 1% rise in students within 30km leads to around 0.09% more such start-ups three years later. The average ward has 54,000 students and 5 high-tech start-ups in a given year, so this implies that 540 students would lead to 0.0045 such start-ups. Perhaps a more illustrative experiment is to consider that a one standard deviation rise in students (a large increase) for the average ward would imply nearly 8% more high-tech start-ups in a given year.[54]

2.5.2.1 Robustness

The core results of high-tech start-ups are robust to altering various assumptions of the baseline specification (Appendix Table 2.B.3), and I also show equivalent robustness tests for total start-ups. First, I experiment with different measures of university presence. Varying the radius for the calculation of total students surrounding a ward reveals that universities appear to have a larger effect on start-ups within a smaller radius of 10km, but there is no effect at a larger radius of 50km. The fact that there is a stronger effect at a more localised level is consistent with findings in the literature.[55] I then use different measures of students, taking total students (giving equal weight to part time students and full time students), normalising by population while still controlling for population, and using unlogged students. The results are broadly unchanged. Alternative assumptions

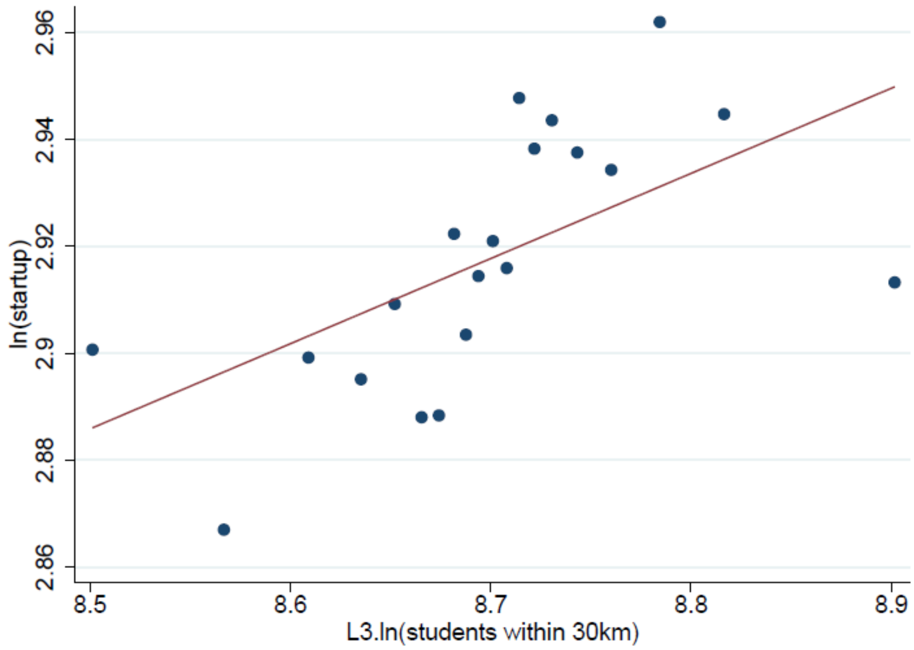
[53] Woodward, Figueiredo and Guimaraes (2006) estimate that a $1 million increase in university R&D expenditures would increase the probability of high-tech manufacturing firm entry by less than 0.1%. Kantor and Whalley (2014) estimate that a 1% increase in university R&D spending leads to an increase in county labour income of 0.08%.

[54] The average ward has 54,000 students, and the standard deviation in 75,000. Increasing the students to 129,000 is an increase of around 88 log points. The implied increase in start-ups in the high-tech sector is therefore $0.09 * 88 = 8\%$.

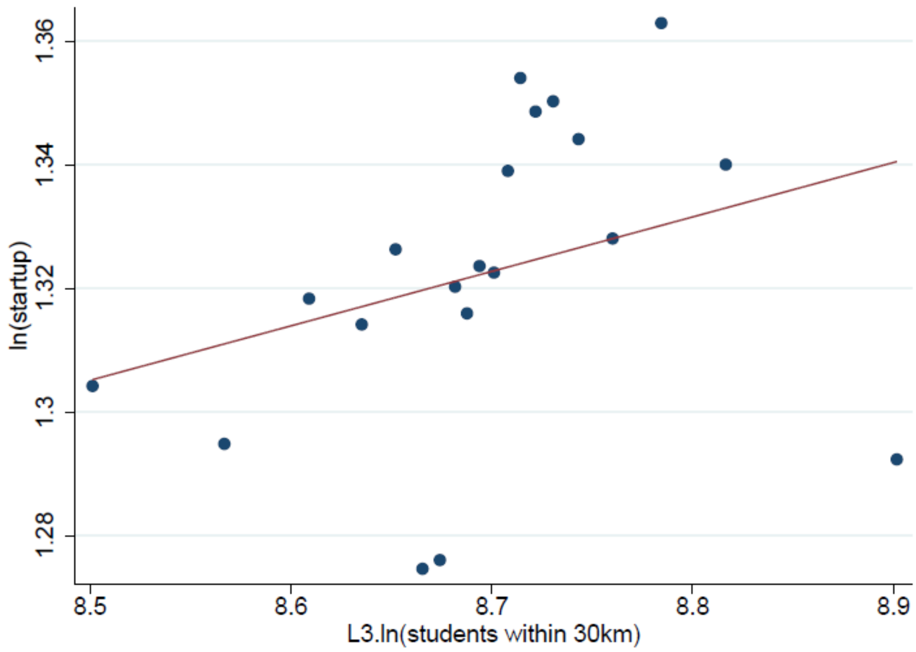
[55] I focus on the 30km radius in this paper for two reasons. First, I want to capture whether there are broader spillovers from universities into local economies, rather than only start-ups which are directly connected to a university (for example student/staff spin-offs). Second, the share of wards that have universities within 10km (36%) is much smaller than at a 30km radius (83%), and I want to retain variation a higher fraction of the sample.

Figure 2.5.1: Universities and Start-Ups

A: Single-unit entrants – all sectors



B: Single-unit entrants – high-tech sectors



NOTES: Scatter plots depict ward level regressions of ln(1+start-ups) on 3 year lagged ln(1+students within 30km), controlling for lagged population within 30km, ward and year fixed effects (so variables are residualised). Data are grouped into equal sized bins with the mean of the variables within each bin plotted in the graphs.

regarding the standard errors have little effect: results are still significant at the 1% level clustering at the local authority level (of which there are 380), and allowing for spatial heteroskedasticity and autocorrelation using Conley standard errors (Fetzer, 2014; Hsiang, 2010) reduces the significance of the high-tech result slightly.

In order to address concerns that these effects are driven by time varying unobservables that changes in population do not capture, such as local government policies or other shocks, I also estimate more demanding specifications including larger area-year fixed effects: at the NUTS1 region, travel to work area and local authority level. With region-year or local-authority-year fixed effects, the effect of universities on high-tech start-ups falls to around 0.05, and is still significant; but including travel to work area – year fixed effects wipes out the results all together. It is likely that variation captured by these dummies is highly co-linear with the changes in enrolments within 30km.

I then consider the effects at different leads and lags of student enrolments, from a one year lead to a five year lag (Appendix Table 2.B.4), and confirm the prior that the 3 year lag is a sensible one to use as it takes time for growth in university size to have an impact. The coefficient on the lead of enrolments is not significant, suggesting that reverse causality is not driving the results. Including all lags together, noting that these measures will be highly co-linear since many of the students enrolled in one year will also be enrolled in the next year, reveals that in fact the fourth lag stands out as the most significant.

2.5.2.2 Heterogeneity

In order to gain more of an understanding about the mechanism underlying the relationship between universities and high-tech start-ups, I examine whether there is any evidence of heterogeneity in the effects by type of university and area. Table 2.5.3 begins with the core result for high-tech start-ups, and then adds the lagged share of students of different type within 30km in columns (2) to (6). Column (1) includes the share of students within 30km that are in Russell Group universities, institutions considered to be of higher quality teaching and research in general. The coefficient on this term is 0.00804, and significant at the 1% level. This suggests that while non Russell Group students have a positive impact on start-ups, every percentage point increase in the share that are at Russell Group universities leads to 0.8% more start-ups. Similarly, the share of postgraduates (a proxy for research intensity) matters for total start-ups. I then consider whether it is postgraduate students in particular disciplines that a driving results, and show that there are positive coefficients on both the share of STEM, medicine related students, and social science, business students, though the STEM, medicine coefficient is not significant. There is also a positive and significant effect of overseas students, which is consistent with evidence from the US that shows that immigrants who enter the country on a student visa are more likely to be entrepreneurs (Hunt, 2011). However, it could also reflect the fact that some overseas students (those from outside the EU) pay higher fees which implies more resource for teaching, research or other university activity - or even that overseas students consume more local goods and services compared to UK students, and with these data, I am unable to disentangle these effects. This last result has implications for the IV strategy, which uses predicted overseas students as an instrument for total students. For exclusion to hold, the instrument should affect the outcome variable (employment) only via its impact on the endogenous variable (total enrolments). I return to this issue below.

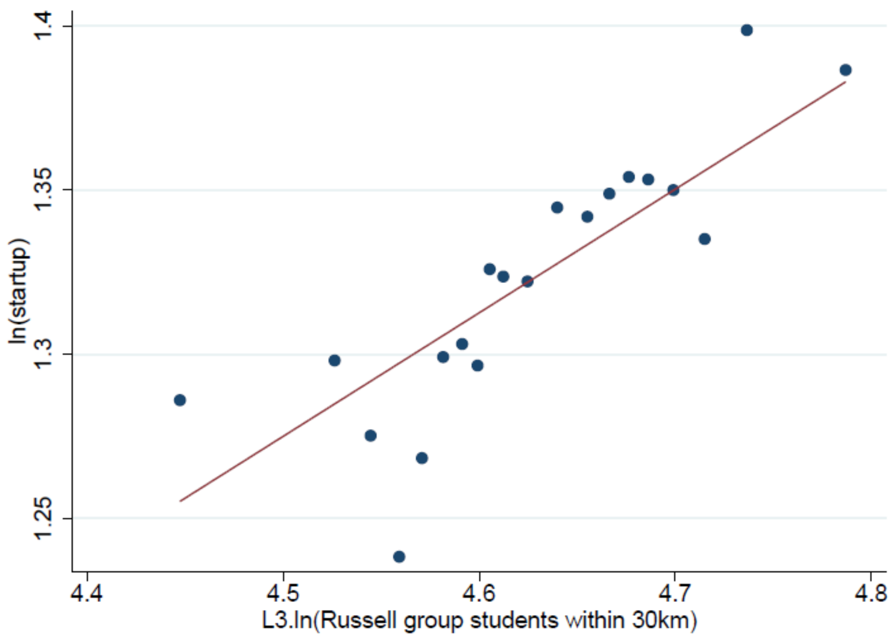
Table 2.5.3: Universities and High-Tech Start-Ups, Differences by University Type

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ln(single-unit entrants, high-tech sectors)						
L3 ln(students, 30km)	0.0882***	0.0905***	0.0879***	0.0872***	0.0834***	0.0464**
	(0.0185)	(0.0185)	(0.0184)	(0.0185)	(0.0185)	(0.0190)
L3 % Russell		0.00804***				
		(0.0013)				
L3 % PG			0.00535***			
			(0.0009)			
L3 % PG STEM, med.				0.00269		
				(0.0018)		
L3 % PG soc sci, bus.					0.00691***	
					(0.0018)	
L3 % Overseas						0.00699***
						(0.0008)
Observations	165,946	165,946	165,946	165,946	165,946	165,946
Clusters	8,734	8,734	8,734	8,734	8,734	8,734

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2016. Column (1) replicates the core regression for high-tech sectors single-unit entrants. Columns (2)-(6) add the lagged share of students within 30km of different types as labelled. "PG" denotes postgraduate students.

The importance of quality and research intensity can also be illustrated by simply using Russell Group students in the measure of university presence (Russell Group students enrolled within 30km). Doing so, the coefficient rises to 0.376, significant at the 1% level, which is over four times the magnitude of the effect of students across all universities. This stronger relationship is depicted in Figure 2.5.2.

Figure 2.5.2: Russell Group Universities and Start-Ups



NOTES: Scatter plots depict ward level regressions of ln(1+start-ups) on 3 year lagged ln(1+Russell Group students within 30km), controlling for lagged population within 30km, ward and year fixed effects (so variables are residualised). Data are grouped into equal sized bins with the mean of the variables within each bin plotted in the graphs.

I also explore whether the results are stronger for particular types of area (urban versus rural), and whether they are driven by a small number of top universities and their associated clusters (Appendix Table 2.B.5). I find that the university effect on high-tech start-ups is much stronger and more significant in urban areas compared to rural areas, consistent with the existence of urban clusters of high-tech activity. Dropping wards in London from the sample does weaken the coefficient slightly but it remains highly significant. Conversely, dropping wards in Cambridge or Oxford does not change the coefficient. Finally, I show that wards with higher initial human capital intensity (measured as a dummy equal to one if the share of population with a degree is greater than the median ward in the initial year[56]) seem to experience higher start-ups as the university sector grows compared to low human capital intensity wards, consistent with there being stronger agglomeration effects in areas that are more likely to pool labour with

[56] There are 928 wards where a series of population with a degree is not available, because the underlying data were missing in the 2001 census. To classify these as high or low human capital areas I compare the 2011 share of the population with a degree to the median in that year.

universities.[57]

Overall, this analysis suggests that while there is a general impact of universities on high-tech start-ups, this is increasing in university quality and research intensity, and higher in high-skill, urban areas. Using these data, it is not possible to disentangle the relative importance of formal collaborations, spin-offs/spin-out activities of university students and staff and associated spillovers, or more informal interactions between the university, its graduates and local industry. Supportive of these effects being at least in part due to graduates staying in the area after their studies, I find that there is a positive and significant relationship between lagged student enrolments and the population with a degree in the same area, and this effect builds over time (Appendix Table 2.B.6).

2.5.2.3 Overseas Students Instrument

The most credible approach is to use the instrument to estimate the effect of overseas students on economic outcomes via two stage least squares. There is little reason to believe that this instrument is related to ward level economic outcomes other than via its predictive power for actual overseas enrolments, so the exclusion restriction appears reasonable in this context. It is harder to argue for exclusion when using this instrument for total enrolments, since as we have seen, overseas students appear to have a differential effect on start-ups. I therefore use the instrument for two purposes: first to estimate the effect of overseas students on high-tech start-ups, and second as another robustness check on the effect of total students. The results are reported in Table 2.5.4.

Panel A begins with the OLS regression of the lag of the natural log of overseas students within 30km on high-tech start-ups and the coefficient is 0.0343, significant at the 1% level. Columns (2) and (3) show that the reduced form and first stage are both strong, and column (4) shows the IV estimate, which is slightly larger than OLS but not very different in magnitude. I take similar steps, instrumenting for total students in Panel B.[58] This time, the IV estimate is over double the OLS estimate, which might seem counter-intuitive if we imagine that more students might be attracted to universities in dynamic, growing areas and therefore we might expect OLS to be biased upwards. However, there could be a negative bias if in fact universities in less dynamic areas have differentially increased

[57] While I focus on the high-tech sectors in this section, the results generally apply for total start-ups across sectors. The main difference is that the start-up result is similar across urban and rural areas, and across high and low human capital areas.

[58] I also construct a placebo test for this instrument, in a long difference format. I split the sample into two periods, and calculate average annual growth in the instrument and outcome for each period. I find that the instrument in the second period does not predict the outcome in the first period.

Table 2.5.4: Universities and High-Tech Start-Ups, IV Estimates

Method	(1) OLS	(2) Reduced Form	(3) First Stage	(4) IV
A: Overseas students				
L3 ln(overseas students, 30km)	0.0343*** (0.0071)			0.0508*** (0.0094)
L3 ln(overseas instrument, 30km)		0.0458*** (0.0084)	0.901*** (0.0091)	
B: All students				
L3 ln(students, 30km)	0.0882*** (0.0185)			0.173*** (0.0317)
L3 ln(overseas instrument, 30km)		0.0458*** (0.0084)	0.265*** (0.0032)	
Observations	165,946	165,946	165,946	165,946
Clusters	8,734	8,734	8,734	8,734

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2016. The dependent variable in columns (1), (2) and (4) is ln(1+ single unit entrants, high-tech sectors). The dependent variable in column (3) is L3 ln(1+overseas students within 30km) in Panel A, and L3 ln(1+students within 30km) in Panel B. Column (1) reports OLS regressions for overseas students within 30km (Panel A) and total students within 30km (Panel B). Columns (2) to (4) show the first stage, reduced form and IV estimates using a shift-share instrument for overseas students.

enrolments (Figure 2.3.2 suggests this could be so). Overall, this analysis suggests that the effects of universities on start-ups are unlikely to be over-estimated.[59]

2.5.3 Universities and Employment, Establishment Level Analysis

We have seen that the effect of universities on ward level employment is positive but not significant, and that the effect on the size of the average establishment is negative, and significant at the 10% level (Table 2.5.1). These effects will in part be driven by changes in composition - as new entrants tend to be smaller in size, but also by changes in the employment of existing establishments at the intensive margin. Establishment level analysis allows me to investigate effects at the intensive margin (changes in employment in existing establishments). In addition, it allows me to examine whether effects differ for different types of establishment. These results are reported in Table 2.5.5, where all columns control for industry – year fixed effects, in addition to establishment level fixed effects and lagged population within 30km.

[59] Results using the alternative instrument calculated at a more aggregated level (EU, non-EU, across all subjects) yield similar estimates and are not reported here.

Table 2.5.5: Universities and Employment, Establishment Level Regressions

Dependent variable: ln(employment)	(1)	(2)	(3)	(4)	(5)
A: 30km radius					
L3 ln(students within 30km)	-0.00894***	-0.00431	-0.00791**	0.0287***	0.272***
	(0.0032)	(0.0033)	(0.0031)	(0.0032)	(0.0049)
L3 ln(students within 30km) X High-tech		-0.0391***			
		(0.0065)			
L3 ln(students within 30km) X young			0.000428***		
			(0.0001)		
L3 ln(students within 30km) X med/large				-1.015***	
				(0.0150)	
L3 ln(students within 30km) X multi					-0.488***
					(0.0061)
A: 50km radius					
L3 ln(students within 50km)	0.0179***	0.0235***	0.0198***	0.0539***	0.331***
	(0.0045)	(0.0045)	(0.0044)	(0.0044)	(0.0058)
L3 ln(students within 50km) X High-tech		-0.0517***			
		(0.0072)			
L3 ln(students within 50km) X young			0.00186***		
			(0.0002)		
L3 ln(students within 50km) X med/large				-1.150***	
				(0.0142)	
L3 ln(students within 50km) X multi					-0.560***
					(0.0062)
Observations	41,803,029	41,803,029	41,803,029	41,803,029	41,803,029
Clusters	8,734	8,734	8,734	8,734	8,734

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2016. All columns include establishment level fixed effects, and industry (SIC 2 digit) X year fixed effects. Panel A uses students within 30km as the university measure, and Panel B uses a 50km radius.

In Panel A, I examine how the employment of establishments that are observed at least twice during the sample period are affected by increases in university enrolments within 30km. Column (1) shows that there is a negative (but small) impact on the employment of the average firm. A 1% increase in students leads to a 0.009% fall in employment. This type of effect could be driven by increased factor and/or product market competition due to establishment entry which would have negative effects on existing, less productive establishments. Column (2) shows that in fact, there is a slightly more negative effect for high-tech establishments, and this is consistent with the evidence of creative destruction in innovative sectors connected with university research in Hausman (2017).[60] Also consistent with this type of mechanism, I find that the effects are less negative for young firms (those under 5 year-old) which have a positive and significant interaction term (column (3)), and it seems that the negative employment effects are driven by larger establishments[61] (column (4)), or those that are part of multi-establishment firms (column (5)).

In Panel B, I show that at a larger radius, where we saw previously the start-up effects are less strong (Appendix Table 2.B.3), there are actually small positive effects on employment for the average establishment. This could be due to the impact of universities on the wider labour market, where the effects of increasing the supply of graduates might counteract the increased demand and competition from start-ups in the immediate area. The patterns of heterogeneity across establishment types however tell the same story as in Panel A: larger, older establishments appear to lose out.

2.5.4 Universities and Productivity

So far, I have shown that universities appear to induce establishment entry in high-tech and other sectors, and that there are small, negative employment effects for existing, larger firms. Given these results, the expected impact of universities on productivity is ambiguous. We might expect a positive impact on productivity for sectors that benefit from innovation, human capital and associated spillovers which universities help generate, but some of these effects might operate at longer lags. In particular, it has been shown that measured revenue productivity of start-ups is often depressed due to lower mark-ups (Foster, Haltiwanger and Syverson, 2008), and start-ups operating in innovative, high-risk

[60] Interestingly, using the same data on firms, Gibbons et al. (2017) find a similar pattern when assessing the impacts on local establishments and employment of changes in road accessibility.

[61] Defined as establishments that have 50 or more employees in the first year in which they are observed in the data.

sectors might take time to start generating revenues and profits. University growth might not affect productivity in sectors where graduates or innovation are less relevant, or there could even be a negative effect if the university and the start-ups it induces create more competition in product and factor markets.

2.5.4.1 Ward Level Productivity Analysis

In Table 2.5.6, ward level panel specifications are built up for GVA per worker and other key measures of performance. Column (1) regresses the natural log of GVA per worker on the university measure and population within the same radius, including also ward and year fixed effects. There is a small positive but insignificant relationship between students and productivity for the average ward. Column (2) includes also capital per worker, which does not change the university coefficient.

Given the preceding analysis, it is interesting to explore whether there might be differential effects for wards that are more high-tech intensive. Interacting the university measure with the share of high-tech establishments in a given year would give rise to "bad control" issues, since we have seen that university growth is associated with high-tech start-ups. I therefore calculate a measure of initial high-tech intensity in a ward, which is the deviation in the share of high-tech establishments in the ward from the median across wards in over the first five years in the sample period.[62] Column (3) interacts this with the university measure, showing that wards with a higher initial high-tech intensity do appear to experience an uplift in productivity as universities grow, though the result is significant only at the 10% level. This result implies that a one per cent rise in university size leads to a 0.06% increase in ward productivity for high-tech intensive wards.[63] Columns (4) and (5) contain other measures of performance as the dependent variable: average wages and profit margin (profit/revenue), with the effect of universities on the average profit margin being positive and significant at the 5% level for high-tech intensive wards.

[62] I use the share of ward level employment in high-tech sectors according to the BSD, as this gives the population of establishments in the ward.

[63] In further analysis (not reported), I find that there are no employment effects based on the ARDx data, which is consistent with the BSD ward level analysis (Table 2.5.1). The positive interaction term with high-tech intensity in column (3) is driven by an increase in GVA which is greater than the increase in employment in high-tech intensive wards.

Table 2.5.6: Universities and Productivity

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	ln(GVA/worker)	ln(GVA/worker)	ln(GVA/worker)	ln(wages/worker)	profit margin
L3 ln(students within 30km)	0.00403	0.0123	-0.0184	-0.0524*	0.0111
	(0.0296)	(0.0284)	(0.0331)	(0.0307)	(0.0147)
L3 ln(students within 30km) x HT intensity			0.0603*	0.0137	0.0218**
			(0.0341)	(0.0316)	(0.0106)
ln(capital/worker)		0.120***	0.120***		
		(0.0041)	(0.0041)		
L3 ln(population within 30km)	-0.0586	-0.15	-0.187	-0.599***	0.142***
	(0.1730)	(0.1660)	(0.1670)	(0.1440)	(0.0491)
Observations	139,891	139,891	139,891	139,891	139,847
Clusters	8,726	8,726	8,726	8,726	8,726

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2014. Standard errors clustered at the ward level in parentheses. All columns include ward level and year fixed effects. "HT intensity" denotes the initial high-tech intensity of the ward, which is a dummy equal to 1 when a ward has higher than median share of high-tech employment in the first 5 years of the data, according to the BSD (which gives the business population).

I investigate further the drivers of the effects of universities on the productivity of their local areas using heterogeneity analysis as before. In Table 2.5.7, I examine heterogeneity in the effect on the productivity of the average ward (Table 2.5.6, panel A, column (2)) by university type, and find that, consistent with the start-ups analysis, university quality appears to matter. In fact the productivity of the average ward benefits from a higher share of Russell Group students, and a higher share of postgraduate medical or STEM students (there are no significant differences of the effects of these shares of different types of students for high-tech intensive wards, so this table reports results for the average ward only). Further analysis using the levels of different types of students (Appendix Table 2.B.7) shows that a 1% increase in Russell Group students leads to a 0.07% increase in the productivity of the average ward.

Table 2.5.7: Universities and Ward Level Productivity, Heterogeneity by University Type

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ln(GVA/emp)						
L3 ln(students, 30km)	0.0123	0.0134	0.0122	0.0114	0.00986	0.00304
	(0.0284)	(0.0284)	(0.0284)	(0.0284)	(0.0284)	(0.0288)
L3 % Russell		0.00315*				
		(0.0017)				
L3 % PG			0.00137			
			(0.0012)			
L3 % PG STEM, med.				0.00442*		
				(0.0025)		
L3 % PG soc sci, bus.					0.00397	
					(0.0026)	
L3 % Overseas						0.00186
						(0.0011)
Observations	139,891	139,891	139,891	139,891	139,891	139891
Clusters	8,726	8,726	8,726	8,726	8,726	8,726

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2014. Standard errors clustered at the ward level in parentheses. Column (1) replicates Table 2.5.6, column (2). Each column adds the lagged share of students within 30km of different types as labelled. "PG" denotes postgraduate.

Some tests of robustness and heterogeneity are reported in the Appendix, based on the result that the core university presence measure has a positive relationship with high-tech intensive ward productivity (Table 2.5.6, column (3)). In general, this result is less robust than the start-up results in subsection 2.5.2, but it survives most alternative assumptions on specification, and remains unchanged even when more granular region - year fixed effects are also included in regressions (Appendix Table 2.B.8).[64] In further analysis I find that in contrast to the start-up results, the productivity result is similar for different lag assumptions, but regressions of the university presence measure on lagged ward productivity, and its interaction with high-tech intensity (to test for evidence of reverse causality) do not yield any significant positive relationships. I also instrument for overseas students and total students using the overseas students instrument (instrumenting also for the endogenous interaction term) and find that the results are of similar order of magnitude (Appendix Table 2.B.9). Finally, consistent with the start-up analysis, the productivity effects appear stronger in urban areas, and are not affected by dropping London, Oxford and Cambridge (Appendix Table 2.B.10). High-tech intensive areas with higher than average initial human capital also appear to have a larger, and more significant university coefficient, again providing evidence that positive effects of universities on high-tech sectors are higher in areas that we may expect to have higher absorptive capacity.

2.5.4.2 Establishment Level Productivity Analysis

Establishment level analysis is reported in the Appendix (Table 2.B.11). This follows a similar structure to the ward level analysis, though now controlling for industry-year fixed effects. The effect of universities on the average establishment is found to be negative, which could be reflective of the mechanism discussed previously whereby incumbents suffer from increased competition. This is unchanged adding capital per worker in column (2). However, column (3) shows that the effect of universities on establishments in the high-tech sectors is positive and significant, and of larger magnitude: a 1% increase in students leads to a 0.17% increase in establishment level productivity. These results are unchanged when the regression are weighted by ward level BSD employment/ward level ARDx employment (Gibbons et al., 2017) which gives increased weight to establishments in wards that are under-represented by sampling and local unit apportionment (result not shown). Average wages and profit margin show a similar pattern to productivity though the effect on wages is small and not significant.[65]

[64] The core regressions employ the natural log of GVA per worker as the dependent variable, as is standard in the literature. Using the inverse hyperbolic since (IHS) transformation, which retains negative GVA per worker observations in the sample (these make up around 5% of all observations in the full sample) makes the main university effect positive, of larger magnitude and significant at the 5% level. The coefficient on the interaction term is now negative and insignificant. Given the large impact of including a small number of observations, this estimate seems less reliable.

[65] Further analysis of additional measures of financial performance also reveals similar results, with positive effects of university growth on output, turnover and capital expenditure per worker measures. In addition, separate regressions of establishment GVA and employment as dependent variables show that the positive coefficient GVA per worker effect for high-tech firms comes from a significant increase in GVA accompanied

The upshot of this analysis is that university presence as defined here does not affect the productivity of surrounding areas on average, but positive effects are felt in areas with higher initial high-tech intensity, and for universities of higher quality and research intensity. At the intensive margin, the productivity of high-tech establishments increases as universities grow.

2.6 Conclusions

In this paper I have shown that universities affect the make-up and performance of industry in their surrounding areas. University growth appears to drive establishment entry across sectors, including in the innovative high-tech sectors, widely considered a key source of future growth. While the average effect is relatively small - a 1% increase in university presence leads to a 0.09% increase in high-tech start-ups - the effect is much larger for higher quality, research intensive institutions: a 1% increase in Russell Group students within 30km leads to nearly a 0.4% increase in high-tech start-ups. A combination of a composition effect (due to new establishment entry) and a small negative effect on existing establishments (consistent with a process of creative destruction), implies that there is little effect on overall employment in local areas.

Positive productivity effects are found only in areas with higher initial high-tech intensity; though growth in higher quality institutions raise productivity even in the average ward. Establishment level analysis also reveals that the productivity of high-tech firms is positive related to university growth. Combined with the results on high-tech start-ups, this analysis suggests that the effects of universities on their local economies are likely to grow over time as industrial composition adjusts.

My findings are consistent with previous literature, which using different measures of university activity and different methods to tackle endogeneity has found that spillovers from universities tend to be felt by particular industries considered to be technologically closer to universities, and are not broad based. In the context of the UK's current industrial strategy, the stronger impacts of higher quality, research intensive universities suggest that the government approach of funding excellence, and stimulating university-business linkages in relevant areas are likely to be fruitful avenues for maximising the impact of universities in local growth strategies. But given the focus on "place" in the industrial strategy, it might also be valuable to build excellence in areas with the industrial potential

by a small, insignificant effect on employment.

to benefit from it. The government's science and innovation audits[66] could be a good mechanism for finding out where this could be so, and for considering how to maximise the benefits from university-firm interactions. Moreover, in addition the role that the UK's top universities play in creating hubs of innovation, other universities might be well-placed to contribute to the diffusion of cutting edge technologies and practices for firms (especially SMEs) that are lagging in their adoption (Haldane, 2018). Raising the productivity of the "long tail" of underperforming firms is key to improving the UK's aggregate and regional productivity performance.

The approach in this paper has its limitations. The measure of university presence based on enrolments is a proxy, and will not capture heterogeneity across universities in terms of their links with local industry or policymakers. In addition, while the heterogeneity analysis suggests that human capital and innovation routes are important, with these data I cannot disentangle these mechanisms and the extent to which they complement each other. Future work will examine in more detail the mechanisms driving these relationships, using data on patents, local labour markets and the extent and types of university-business interaction together with institutional features which make these more effective. It will also be interesting to consider whether there are differences in the economic impact of further education colleges compared to universities, using equivalent data on their enrolments.

As new versions of the financial microdata become available, I intend to refine the capital stocks estimates, and therefore carry out some more rigorous analysis of TFP using alternative estimation methods.

Finally, a number of recent policy changes might also form the basis of natural experiments, generating plausibly exogenous variation in enrolments in different universities, which could feed through to local firms over these coming years. Potential candidates include the lifting of student caps in over the period 2012-2015 and changes in overseas enrolments following the EU referendum in 2016.

[66] See: https://www.gov.uk/government/publications/science-and-innovation-audits-second-reports-published

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2.A Data Appendix

2.A.1 University Data

I obtained administrative data on all students at higher education institutions between the academic years 1994/1995 and 2015/16 from the Higher Education Statistics Authority (HESA). For each institution and each year, the number of students (as at 1st December) are broken down by level of study, gender, subject area, country of domicile and mode of study. Institutions are merged with a listing of UK universities from the World Higher Education Database (WHED) (Valero and Van Reenen, 2018) which gives university postcodes and hence allows them to be geocoded. For the purposes of this paper, institutions in Northern Ireland are excluded, as firm level data are available for Great Britain only.

Data are provided for the institutions using their names in a given year, and in order to create a Panel it is necessary to correct for name changes and mergers. Analysis is based on their form in the most recent year of data. HESA data are collected for higher education institutions, which includes some specialist higher education colleges in addition to universities, and there are a number of institutions that enter the data during the period. Those institutions are excluded from the analysis. The university sample of 136 institutions is given below, together with founding date (either the date that the institution was first set up in its original form, or the date it joined the HE sector, based on availability in the World Higher Education Database, and manual web searches).

University sample: The University of Oxford (1167), The University of Cambridge (1209), The University of St Andrews (1413), The University of Glasgow (1451), The University of Aberdeen (1495), The University of Edinburgh (1583), St George's, University of London (1751), The Royal Veterinary College (1791), The University of Strathclyde (1796), Heriot-Watt University (1821), Royal Academy of Music (1822), Liverpool John Moores University (1823), Birkbeck College (1823), The University of Manchester (1824), University College London (1826), The University of Central Lancashire (1828), King's College London (1829), University of Durham (1832), Newcastle University (1834), University of London (Institutes and activities) (1836), Royal College of Art (1837), The University of Westminster (1838), University of Chester (1839), The University of Winchester (1840), York St John University (1841), University of South Wales (1841), University of St Mark and St John (1841), Roehampton University (1841), Liverpool Hope University (1844), Royal Conservatoire of Scotland (1845), London Metropolitan University (1848), St Mary's University, Twickenham (1850), University of Derby (1851), University of Wales Trinity Saint David (1853), Southampton Solent University (1856), Anglia Ruskin University (1858), The University of West London (1860), The University of Lincoln (1861), Bishop Grosseteste University (1862), The University of Southampton (1862), Cardiff Metropolitan University (1865), University for the Creative Arts (1866), The University of Portsmouth (1870), Aberystwyth University (1872), Trinity Laban Conservatoire of Music and Dance (1872), The University of Birmingham (1875), Glasgow Caledonian University (1875), The University of Bristol (1876), The University of Dundee (1881), The University of Liverpool (1881), University of Nottingham (1881), Royal College of Music (1882), The University of

Bradford (1882), Cardiff University (1883), Bangor University (1884), The University of Leeds (1884), Queen Mary University of London (1885), Edge Hill University (1885), Royal Holloway and Bedford New College (1886), Glyndŵr University (1887), University of Abertay Dundee (1888), The University of Greenwich (1890), The University of Brighton (1890), Goldsmiths College (1891), The University of Surrey (1891), The University of Reading (1892), London South Bank University (1892), The University of East London (1893), Royal Northern College of Music (1893), Writtle University College (1893), Buckinghamshire New University (1893), The University of Bath (1894), City, University of London (1894), London School of Economics and Political Science (1895), Aston University (1895), De Montfort University (1896), The University of Salford (1896), The University of Sheffield (1897), The University of the West of Scotland (1897), London School of Hygiene and Tropical Medicine (1899), Harper Adams University (1901), Falmouth University (1902), The Robert Gordon University (1903), The Royal Central School of Speech and Drama (1906), Imperial College of Science, Technology and Medicine (1907), University of Bedfordshire (1908), Loughborough University (1909), The School of Oriental and African Studies (1916), Swansea University (1920), The University of Leicester (1921), The University of Exeter (1922), The University of Hull (1927), Teesside University (1929), University of Worcester (1946), Cranfield University (1946), Keele University (1949), University of Hertfordshire (1952), Brunel University London (1957), The University of Sussex (1961), Canterbury Christ Church University (1962), The University of York (1963), The University of East Anglia (1963), Edinburgh Napier University (1964), The University of Essex (1964), University of Cumbria (1964), The University of Lancaster (1964), The University of Kent (1964), The University of Warwick (1965), London Business School (1965), Leeds Trinity University (1966), The University of Stirling (1967), Newman University (1968), Sheffield Hallam University (1969), University of Northumbria at Newcastle (1969), University of the West of England, Bristol (1969), The University of Wolverhampton (1969), The University of Sunderland (1969), Coventry University (1970), The Nottingham Trent University (1970), Kingston University (1970), Staffordshire University (1970), University of Plymouth (1970), The Manchester Metropolitan University (1970), Oxford Brookes University (1970), Leeds Beckett University (1970), The University of Huddersfield (1970), Birmingham City University (1971), Queen Margaret University, Edinburgh (1971), Middlesex University (1973), Bath Spa University (1975), Bournemouth University (1976), The University of Chichester (1976), The University of Northampton (1977), The University of Bolton (1982), University of the Arts, London (1986), University of Gloucestershire (1990).

Institutions in HESA not included in the list include: Open University (not spatially meaningful); Northern Ireland universities (because only Great Britain analysed in this paper): The Queen's University Belfast, University of Ulster, Stranmillis University College, St Mary's University College; specialist colleges which are not government recognised, or only recently recognised (https://www.gov.uk/check-a-university-is-officially-recognised): Bell College, Conservatoire for Dance and Drama, Leeds College of Music, The Liverpool Institute for Performing Arts, The National Film and Television School, Plymouth College of Art, Leeds College of Art; The Royal College of Nursing (because it is multi-location and considered a nursing union), The University of Wales (central functions) as data available only for 2 years and under 5 students.

The following recognised institutions are dropped because data are not available in HESA for the full 22 years (as they joined the HE sector more recently) and their inclusion would create arbitrary jumps as they all grew out of pre-existing institutions: Royal Agricultural University, University of the Highlands and Islands, The Arts University Bournemouth, University of Suffolk, University College Birmingham, The University of Buckingham, Guildhall School of Music and Drama, Norwich University of the Arts, and Heythrop College. University Campus Suffolk and University of the Highlands and Islands are slight exceptions, as their founding dates are 2001 and 2007 respectively. But both relate to multi-site institutions so spatial analysis is less meaningful, and in both cases many of the sites were pre-existing colleges.

Subjects of study are categorised into JACS subject codes, and these were aggregated into 19 major subject groups in the data obtained for this study. I further aggregate these into six subject groups (Table 2.B.12). There are two reasons for this: first to try to group subjects that we might expect to have particular relevance for local firms for heterogeneity analysis; and second in order to have sufficient overseas students in the early years when there were fewer overseas students for the calculation of the overseas instrument (Machin and Murphy, 2017).

2.A.2 Firm Level Data

Administrative data on establishments: Data for the analysis of ward level employment and number of establishments, and establishment-level employment is based on the Inter-Departmental Business Register (IDBR). The IDBR is a live record of VAT or PAYE registered businesses, accessed via the Business Structure Database (BSD) which provides an annual snapshot of the register.[67] Data are divided into "local units" (the establishment) and "enterprises" (the overall business organisation, some of which consist of more than one establishment or business site). Since this paper examines spatial relationships between firms and universities, the establishment is the relevant unit of analysis.

The basis of the analysis is a cleaned, unbalanced panel of live establishments over the period 1997 to 2016. The key variables used in this paper are the establishment's postcode, industry, employment, birth and death dates, and whether or not the establishment belongs to a multi-unit enterprise, or a multinational. The establishment birth and death dates are used in the analysis of establishment entry or exit. An establishment is considered to be a new entrant if it is the first year that it enters the Panel, and the birth-date is within 3 years previous to it entering the Panel. An establishment is considered to be exiting in

[67] Office for National Statistics. (2017). Business Structure Database, 1997-2017: Secure Access. [data collection]. 9th Edition. UK Data Service. SN: 6697, http://doi.org/10.5255/UKDA-SN-6697-9

its last year before its "death" date. A variable is constructed to indicate whether firms are single-establishment or multi-establishment (defined as being part of multi-unit, or foreign owned enterprises).

Establishment postcodes are mapped to 2015 electoral ward using the ONS postcode directory. Where employment is missing for an establishment which re-enters the data in subsequent years, employment is interpolated. For the ward level analysis, the number of live local units, entrants, and their employment are collapsed by ward each year to create a ward level Panel. Industry codes are also used here to calculate the ward's employment or establishments by sector for each year. For consistency the analysis based on the IDBR uses 2003 SIC codes throughout.

In the establishment level analysis, local units that change address are considered to be new local units. Therefore all variation in the university presence measure comes from expansion of universities, rather than establishments moving location. In addition, only non-interpolated data are used in this analysis.

Financial survey data: Financial data are available for a sample of firms in the IDBR from the "Annual Business Survey" (ABS), which covers the production, construction, distribution and service industries representing approximately two thirds of the UK economy. Parts of the agricultural sector, the financial sector; and public administration and defence, activities of households as employers and extra-terrestrial organisations are excluded by the ABS. The ABS also excludes public sector activities in the education and health sectors. The ABS contains the population of larger businesses, and a random sample of smaller businesses. The ABS has been carried out since 2009, and is combined with employment data from the UK business and employment survey (BRES). Its predecessor the "Annual Business Inquiry" (ABI) included an employment survey and was used to create the "Annual Respondents Database" (ARD). In this paper, I use the "ARDx"[68], which combines and harmonises variables in the ABS and ABI over the period 1998-2015.[69] Data for Northern Ireland are not available in the UK Data Archive.

Financial data are collected for the "reporting unit" of the firm, and needs to be apportioned to the local unit level. As is standard in the literature (for example, Gibbons et al. (2017)) this is done using an establishment's share of total enterprise employment.

[68] Office for National Statistics. Virtual Microdata Laboratory (VML), University of the West of England, Bristol. (2017). Annual Respondents Database X, 1998-2015: Secure Access. [data collection]. 4th Edition. Office for National Statistics, [original data producer(s)]. UK Data Service. SN: 7989, http://doi.org/10.5255/UKDA-SN-7989-4

[69] For a description of the ARDx, see http://doc.ukdataservice.ac.uk/doc/7989/mrdoc/pdf/7989_ardx_userguide.pdf

Note that in about 80% of reporting units, the reporting unit is a single establishment and located entirely at a single address, so the financial data corresponds exactly to the local unit and no apportionment is necessary. However, the share of local units that are part of single-unit reporting units is smaller, because of the fact that larger businesses are over-represented in the sample, and also the effects of large firms with high numbers of plants.

The key financial variable used in this paper is labour productivity, defined as GVA (in basic prices) per worker, but I also obtain information on investment, wages, turnover, output and profitability. In addition, I estimate capital stocks using the ARDx methodology, which is still under development.[70] Financial variables are converted into real terms using ONS sectoral deflators (Experimental Industry (Division) Level Deflators, ONS, 2010=100), and capital is deflated using deflators by asset class and sector (Volume Index of UK Capital Services (experimental): Estimates to 2015, ONS; 2013=100). The ARDx provides industry codes using SIC2007 throughout the sample period 1998-2015. For the ward level analysis, missing values of surviving establishments are interpolated, and ward totals of financial variables and employment based on local units with financial data (surveyed or apportioned) are calculated and then variables are normalised by employment (apart from profits which are normalised by turnover to calculate a standard profit margin).

In the establishment level analysis, only non-missing values are used, and as with the BSD, local units that change address are considered to be new local units so that all variation in the university presence measure comes from expansion of universities, rather than establishments moving location. In addition, GVA/worker and wages/worker are winsorised for the the top and bottom 1% observations in each year.

2.A.3 Mapping High-Tech Sectors

High-tech sectors are mapped according to classifications given by NESTA (Bakhshi et al., 2015). These build on Eurostat classifications (based on R&D spend in manufacturing, and knowledge intensity – as measured by the qualifications of the workforce – for services), but use also the STEM intensity of occupations within different sectors to build a more holistic picture of the UK's high-tech industries. These mappings are provided using SIC2007 3 and 4 digit codes, and therefore can be mapped directly in the ARDx where these codes are available throughout the sample period. I manually map the sectors at the

[70] For a description, see http://doc.ukdataservice.ac.uk/doc/7989/mrdoc/pdf/7989_ardx_capital_stock_userguide.pdf

equivalent level to their SIC2003 counterparts in order to obtain an equivalent high-tech classification for the BSD. The exact mappings are shown in Table 2.B.13. The only areas of inconsistency are that it is not possible to split out "Engineering activities and related technical consultancy" and "Other professional, scientific and technical activities n.e.c." from "Architectural and engineering activities and related technical consultancy"; and reinsurance from "Insurance and pension funding, except compulsory social security" in the SIC2003 mapping.

2.A.4 Population Data

The key area level control in this analysis is population within the same radius as the university measure (a given radius from the centroid of the ward). In obtain population data from the census in 2001 and 2011, at the Lower Super Output Area (LSOA) level for England and Wales (these are referred to as Data Zones (DZ) in Scotland). In some cases, these areas differ between the two census years. When merging LSOA 2001 with LSOA 2011, I have to deal with cases where one LSOA 2001 is split into many LSOA2011. I do this by splitting population equally into all the new LSOA. The reverse is easier to deal with. If many LSOA 2001 are aggregated into one LSOA 2011, I simply collapse to the new area. Finally, I map the data in LSOA 2011 terms to electoral ward using the NSPD 2015. The data from 2011 and 2011 are interpolated and extrapolated to fill the sample period in the analysis.

2.B Appendix Tables

Table 2.B.1: Establishment Level Descriptive Statistics

	Mean	SD
A: BSD plants sample (N=41,803,029)		
Employment	11	71
Postcode urban	0.72	0.45
London	0.16	0.36
Plant is high-tech	0.15	0.35
Plant is young (<=5 years)	0.37	0.48
Plant is large (>=50 employees)	0.03	0.17
Plant is multi-unit	0.47	0.5
Students within 30km	79,687	98,637
Population within 30km	2,960,642	2,992,696
B: ARDx plants sample (N=3,241,842)		
GVA per worker	38,543	42,224
Employment	41	147
Postcode urban	0.87	0.34
London	0.14	0.34
Plant is high-tech	0.06	0.24
Plant is young (<=5 years)	0.23	0.42
Plant is large (>=50 employees)	0.16	0.36
Students within 30km	75,004	90,316
Population within 30km	2,849,935	2,770,761

NOTES: Panel A summarises the BSD sample, based on an unbalanced panel of live establishments over the years 1998-2016. Panel B summarises the ARDx sample, based on an unbalanced panel of establishments over the years 1998-2014 (for which capital stock is available). "Establishments" are defined as local unit (luref)-postcode pairs. So if a local unit moves location it is considered to be a new establishment. Panel A relates to observations on 7.4 million "establishments", and Panel B relates to observations on 644,430 "establishments". Singletons (establishments that are only observed for one year) are excluded from the establishments samples. Observations with missing employment or financial data are excluded from the establishments samples. The university measures are based on the co-ordinates of the establishment postcode. "High-tech" is a dummy=1 if an establishment has been classified as operating in the high tech sectors at least once in the sample period. "Young" is a dummy=1 if an establishment is 5 years old or younger in a given year. "med/large" is a dummy=1 if the establishment has employment of 50 or more in its first observation. "multi" is a dummy = 1 if an establishment has been part of a multi-unit enterprise during the sample period.

Table 2.B.2: Basic Correlations, Nearest University Quality

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ln(establishments)		ln(employment)		ln(entrants)	
ln(distance to closest uni)	-0.142***	-0.0620***	-0.247***	-0.187***	-0.213***	-0.153***
	(0.0133)	(0.0200)	(0.0175)	(0.0273)	(0.0135)	(0.0202)
ln(distance to closest uni) x Russell	-0.100***		-0.126***		-0.103***	
	(0.0264)		(0.0360)		(0.0276)	
Russell	0.380***		0.525***		0.383***	
	(0.0740)		(0.1010)		(0.0762)	
ln(distance to closest uni) x percent 4* in REF		-0.00505***		-0.00424***		-0.00402***
		(0.0008)		(0.0011)		(0.0009)
percent 4* in REF		0.0183***		0.0175***		0.0164***
		(0.0023)		(0.0032)		(0.0024)
population within 30km	0.202***	0.200***	0.192***	0.191***	0.358***	0.356***
	(0.0091)	(0.0092)	(0.0116)	(0.0117)	(0.0095)	(0.0096)
Observations	8,734	8,734	8,734	8,734	8,734	8,734

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Cross sectional regressions for 2016 (latest year in the BSD) only, N=8,734 ward level observations for all regressions. Regressions contain no additional controls. Robust standard errors in parentheses. Columns (1) and (2) show regressions of ward level number of establishments on distance to closest university. This measure is interacted with a dummy indicating whether the closest university is in the Russell Group in Column (1), and by the percent of research rated 4 star by the REF (average of all departments weighted by full time equivalent staff in each department) in Column (2). The same exercise is performed with the dependent variables shown in the remainder of the columns.

Table 2.B.3: Universities and Start-Ups, Summary of Robustness Tests

		(1)	(2)		
	Dependent variable:	ln(HT start-ups)	ln(all start-ups)	N	Clusters
	Specification				
A	L3 ln(students, 30km)	0.0882***	0.160***	165,946	8,734
		(0.0185)	(0.0152)		
B	L3 ln(students, 10km)	0.274***	0.271***	165,946	8,734
		(0.0196)	(0.0159)		
C	L3 ln(students, 50km)	-0.104***	-0.0143	165,946	8,734
		(0.0257)	(0.0208)		
D	L3 ln(FT+PT students, 30km)	0.0910***	0.160***	165,946	8,734
		(0.0179)	(0.0145)		
E	L3 students/pop, 30km	0.0298***	0.0402***	165,946	8,734
		(0.0078)	(0.0064)		
F	L3 students, 30km (000)	0.0492***	0.263***	165,946	8,734
		(0.0060)	(0.0230)		
	Standard Errors				
G	L3 ln(students, 30km)	0.0882***	0.160***	165,946	380
		(0.0199)	(0.0151)		
H	L3 ln(students, 30km)	0.0882**	0.160***	165,946	
		(0.0401)	(0.0390)		
	Fixed Effects				
I	L3 ln(students, 30km)	0.0535***	0.124***	165,946	8,734
		(0.0179)	(0.0147)		
J	L3 ln(students, 30km)	-0.0319	0.0232	165,737	8,723
		(0.0267)	(0.0214)		
K	L3 ln(students, 30km)	0.0516*	0.0871***	165,946	8,734
		(0.0276)	(0.0213)		

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2016. Row A repeats the core specification as per Table 2.5.2 for high-tech start-ups and those across sectors. Rows B and C replicate the core regressions using different radius for the calculation of total students. Row D uses total students, rather than FTE students. Row E normalises students by population, as well as controlling for population. Row F uses unlogged students (in 1000s). Row G clusters standard errors at the local authority level (of which there are 380). Row H estimates Conley standard errors to allow for spatial heteroskedastity and autocorrelation (Fetzer (2014) and Hsiang (2010)), with a distance cut-off of 30km. Row I includes region-year fixed effects. Row J includes travel to work area–year fixed effects (209 singleton observations are dropped). Row K includes local authority-year fixed effects.

Table 2.B.4: Universities and High-Tech Start-Ups, Different Lags

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: ln(single-unit entrants, high-tech sectors)								
F1 ln(students, 30km)	0.0108							-0.164***
	(0.0253)							(0.0510)
ln(students, 30km)		0.0511**						-0.0187
		(0.0250)						(0.0706)
L1 ln(students, 30km)			0.0900***					0.0627
			(0.0249)					(0.0676)
L2 ln(students, 30km)				0.122***				0.0868
				(0.0255)				(0.0670)
L3 ln(students, 30km)					0.135***			0.0609
					(0.0265)			(0.0673)
L4 ln(students, 30km)						0.131***		0.173***
						(0.0265)		(0.0642)
L5 ln(students, 30km)							0.0809***	-0.151***
							(0.0258)	(0.0488)
Observations	113,542	113,542	113,542	113,542	113,542	113,542	113,542	113,542
Clusters	8,734	8,734	8,734	8,734	8,734	8,734	8,734	8,734

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. The regressions are carried out on a balanced sample for comparability of the effects of different lags of the university variable.

Table 2.B.5: Universities and High-Tech Start-Ups, Differences by Area

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: ln(single-unit entrants, HT sectors)									
L3 ln(students, 30km)	0.0882***	0.104***	0.028	0.0599***	0.0900***	0.0883***	0.0627***	0.108***	0.0605**
	(0.0185)	(0.0280)	(0.0245)	(0.0183)	(0.0185)	(0.0185)	(0.0183)	(0.0262)	(0.0257)
L3 ln (population, 30km)	0.449***	0.932***	-0.792***	-0.899***	0.441***	0.449***	-0.920***	1.613***	-0.750***
	(0.1200)	(0.1540)	(0.1870)	(0.1340)	(0.1200)	(0.1200)	(0.1340)	(0.1530)	(0.1820)
Observations	165,946	96,786	69,160	153,520	165,680	165,490	152,798	81,548	84,398
Clusters	8,734	5,094	3,640	8,080	8,720	8,710	8,042	4,292	4,442
Sample	All	Urban	Rural	Drop Lon	Drop Cam	Drop Ox	Drop Lon, Cam, Ox	high initial HC	low initial HC

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2016. Standard errors clustered at the ward level in parentheses. Samples are as indicated.

Table 2.B.6: Universities and Graduate Population

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ln(population with a degree within 30km)						
L1 ln(students, 30km)	0.100***					-0.207***
	(0.0185)					(0.0439)
L2 ln(students, 30km)		0.123***				-0.0406
		(0.0182)				(0.0567)
L3 ln(students, 30km)			0.167***			0.688***
			(0.0176)			(0.0673)
L4 ln(students, 30km)				0.0998***		-1.491***
				(0.0185)		(0.0774)
L5 ln(students, 30km)					0.317***	1.251***
					(0.0261)	(0.0703)
Observations	157,212	148,478	139,744	131,010	122,276	122,276
Clusters	8,734	8,734	8,734	8,734	8,734	8,734

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level.

Table 2.B.7: Universities and Ward Level Productivity, Heterogeneity by Student Type in Levels

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ln(GVA/emp)						
L3 ln(students, 30km)	0.0123					
	(0.0284)					
L3 ln(Russell, 30km)		0.0689**				
		(0.0296)				
L3 ln(PG, 30km)			0.0242***			
			(0.0091)			
L3 ln(PG STEM, med., 30km)				0.0202**		
				(0.0081)		
L3 ln(PG soc. sci, bus., 30km)					0.00821	
					(0.0070)	
L3 ln(Overseas, 30km)						0.0182*
						(0.0106)
Observations	139,891	139,891	139,891	139,891	139,891	139,891
Clusters	8,726	8,726	8,726	8,726	8,726	8,726

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2014. Standard errors clustered at the ward level in parentheses. Column (1) replicates Table 2.5.6, column (2). In the remaining columns, different populations of students are included in the university presence variable are as labelled. "PG" denotes postgraduate students.

Table 2.B.8: Universities and Ward Level Productivity, Summary of Robustness Tests

		(1)	(2)		
		Coefficient on:			
	University variable	Uni var	Uni var x HT	N	Clusters
	Specification				
A	L3 ln(students, 30km)	-0.0184	0.0603*	139,891	8726
		(0.0331)	(0.0341)		
B	L3 ln(students, 10km)	-0.000893	0.00752	139,891	8726
		(0.0392)	(0.0470)		
C	L3 ln(students, 50km)	-0.0353	0.0577*	139,891	8726
		(0.0433)	(0.0349)		
D	L3 ln(FT+PT students, 30km)	-0.0298	0.0651*	139,891	8726
		(0.0316)	(0.0338)		
E	L3 students/pop., 30km	-0.0179	0.0234	139,891	8726
		(0.0147)	(0.0180)		
F	L3 students, 30km (000)	0.000242	-0.0000813	139,891	8726
		(0.0004)	(0.0004)		
G	L3 ln(students, 30km)	-0.0353	0.0966*	139,891	8,726
		(0.0362)	(0.0495)		
H	L3 ln(students, 30km)	0.298**	-0.111	141,647	8,728
		(0.1460)	(0.1460)		
	Standard Errors				
I	L3 ln(students, 30km)	-0.0184	0.0603*	139,891	380
		(0.0336)	(0.0352)		
J	L3 ln(students, 30km)	-0.0184	0.0603***	139,891	
		(0.0134)	(0.0124)		
	Fixed Effects				
K	L3 ln(students, 30km)	-0.0286	0.0658*	139,891	8,726
		(0.0341)	(0.0345)		
L	L3 ln(students, 30km)	-0.049	0.0559	139,698	8,715
		(0.0495)	(0.0357)		
M	L3 ln(students, 30km)	-0.015	0.0698*	139,891	8,726
		(0.0536)	(0.0365)		

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2014. Standard errors clustered at the ward level in parentheses. Row A replicates Table 2.5.6, column (3). Rows B and C do the same using different radius for universities. Row D uses total students rather than FTE. Row E normalises students by population, and also controls for population separately. Row F uses unlogged students in 1000s. Row G includes also an interaction term between population and ST share. Row H uses the IHS transformation to retain negative GVA values of GVA/worker. Row I clusters standard errors at the local authority level. Row J uses Conley standard errors. Row K includes region-year fixed effects. Row M includes travel to work area–year fixed effects. Row M includes local authority–year fixed effects. "HT" denotes the initial high-tech intensity of the ward, which is a dummy equal to 1 when a ward has higher than median share of high-tech employment in the first 5 years of the data, according to the BSD (which gives the business population).

Table 2.B.9: Universities and Ward Level Productivity, IV Estimates

Method	(1) OLS	(2) Reduced Form	(3) IV
A: Overseas students			
L3 ln(overseas students, 30km)	0.00426		-0.00103
	(0.0125)		(0.0163)
L3 ln(overseas students, 30km) X HT	0.0283**		0.0344**
	(0.0131)		(0.0147)
L3 ln(overseas instrument, 30km)		0.00015	
		(0.0146)	
L3 ln(overseas instrument, 30km) X HT		0.0299**	
		(0.0127)	
B: Total students			
L3 ln(students, 30km)	-0.0184		0.0114
	(0.0331)		(0.0554)
L3 ln(students, 30km) X HT	0.0603*		0.0955**
	(0.0341)		(0.0404)
L3 ln(overseas instrument, 30km)		0.00015	
		(0.0146)	
L3 ln(overseas instrument, 30km) X HT		0.0299**	
		(0.0127)	
Observations	139,891	139,891	139,891
Clusters	8,726	8,726	8,726

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. "HT" denotes the initial high-tech intensity of the ward, which is a dummy equal to 1 when a ward has higher than median share of high-tech employment in the first 5 years of the data, according to the BSD (which gives the business population).

Table 2.B.10: Universities and Ward Level Productivity, Heterogeneity by Area Type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: ln(GVA per worker)									
L3 ln(students, 30km)	-0.0184	-0.0315	0.0144	-0.0266	-0.0165	-0.0193	-0.0258	-0.0454	0.00109
	(0.0331)	(0.0411)	(0.0545)	(0.0336)	(0.0331)	(0.0330)	(0.0336)	(0.0519)	(0.0427)
L3 ln(students, 30km) x HT	0.0603*	0.0745*	0.0304	0.0679*	0.0605*	0.0613*	0.0694*	0.0989*	0.0267
	(0.0341)	(0.0410)	(0.0599)	(0.0356)	(0.0341)	(0.0341)	(0.0356)	(0.0520)	(0.0455)
Observations	139,891	82,432	57,459	129,085	139,674	139,520	128,497	68,455	71,383
Clusters	8,726	5,092	3,634	8,072	8,712	8,702	8,034	4,292	4,429
Sample	All	Urban	Rural	Drop Lon	Drop Cam	Drop Ox	Drop Lon, Cam, Ox	high initial HC	low initial HC

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2014. Standard errors clustered at the ward level in parentheses. Column (1) replicates Table 2.5.6, column (3) and in the remaining columns, this specification is applied to samples as indicated. "HT" denotes the initial high-tech intensity of the ward, which is a dummy equal to 1 when a ward has higher than median share of high-tech employment in the first 5 years of the data, according to the BSD (which gives the business population).

Table 2.B.11: Universities and Establishment Level Productivity

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	ln(GVA/worker)	ln(GVA/worker)	ln(GVA/worker)	ln(wages/worker)	profit margin
L3 ln(students, 30km)	-0.0260**	-0.0315***	-0.0405***	-0.00375	-0.0828
	(0.0115)	(0.0118)	(0.0121)	(0.0098)	(0.1250)
L3 ln (students, 30km) x High-tech			0.169***	0.000919	0.791***
			(0.0385)	(0.0396)	(0.2790)
L3 ln (capital/worker)		0.146***	0.146***		
		(0.0023)	(0.0023)		
L3 ln (population, 30km)	0.207***	0.157**	0.157**	-0.138**	1.869*
	(0.0642)	(0.0649)	(0.0649)	(0.0558)	(1.0740)
Observations	3,241,842	3,241,842	3,241,842	3,241,842	3,226,866
Clusters	8,712	8,712	8,712	8,712	8,712

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Panel regressions over the period 1998-2014. Standard errors clustered at the ward level in parentheses. All columns include establishment level fixed effects and industry (2 digit) X year fixed effects. "High-tech" is a dummy=1 if an establishment has been classified as operating in the high tech sectors at least once in the sample period.

Table 2.B.12: Subject Groups

JACS subject area	Five subject groups
(1) Medicine & dentistry	Medicine, dentistry and allied subjects
(2) Subjects allied to medicine	Medicine, dentistry and allied subjects
(3) Biological sciences	STEM
(4) Veterinary science	Medicine, dentistry and allied subjects
(5) Agriculture & related subjects	Medicine, dentistry and allied subjects
(6) Physical sciences	STEM
(7) Mathematical sciences	STEM
(8) Computer science	STEM
(9) Engineering & technology	STEM
(A) Architecture, building & planning	Creative arts, design, education and other
(B) Social studies	Social sciences, law and business
(C) Law	Social sciences, law and business
(D) Business & administrative studies	Social sciences, law and business
(E) Mass communications & documentation	English, language, history
(F) Languages	English, language, history
(G) Historical & philosophical studies	English, language, history
(H) Creative arts & design	Creative arts, design, education and other
(I) Education	Creative arts, design, education and other
(J) Combined	Combined

Table 2.B.13: High-Tech Industry Codes

SIC07	SIC 2007 industry name	SIC03	SIC 2003 industry name
610	Extraction of crude petroleum	1110	Extraction of crude petroleum and natural gas
910	Support activities for petroleum and natural gas extraction	1120	Service activities incidental to oil and gas extraction excluding surveying
1820	Reproduction of recorded media	2230	Reproduction of recorded media
1920	Manufacture of refined petroleum products	2320	Manufacture of refined petroleum products
2013	Manufacture of other inorganic basic chemicals	2413	Manufacture of other inorganic basic chemicals
2059	Manufacture of other chemical products n.e.c.	2466	Manufacture of other chemical products not elsewhere classified
2110	Manufacture of basic pharmaceutical products	2441	Manufacture of basic pharmaceutical products
2120	Manufacture of pharmaceutical preparations	2442	Manufacture of pharmaceutical preparations
2452	Casting of steel	2752	Casting of steel
2611	Manufacture of electronic components	3210	Manufacture of electronic valves and tubes and other electronic components
2620	Manufacture of computers and peripheral equipment	30	Manufacture of Office Machinery and Computers
2630	Manufacture of communication equipment	32	Manufacture of Radio, Television and Communication Equipment and Apparatus
2640	Manufacture of consumer electronics	31	Manufacture of Electrical Machinery and Apparatus Not Elsewhere Classified
2651	Manufacture of instruments and appliances for measuring, testing and navigation	3320,	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment & Manufacture of industrial process control equipment
		3330	
2660	Manufacture of irradiation, electromedical and electrotherapeutic equipment	3310	Manufacture of medical and surgical equipment and orthopaedic appliances
2670	Manufacture of optical instruments and photographic equipment	3340	Manufacture of optical instruments and photographic equipment

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SIC07	SIC 2007 industry name	SIC03	SIC 2003 industry name
2752	Manufacture of non-electric domestic appliances	2972	Manufacture of non-electric domestic appliances
2811	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines	2911	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
2894	Manufacture of machinery for textile, apparel and leather production	2954	Manufacture of machinery for textile, apparel and leather production
3030	Manufacture of air and spacecraft and related machinery	3530	Manufacture of aircraft and spacecraft
3316	Repair and maintenance of aircraft and spacecraft	3530	Manufacture of aircraft and spacecraft
3511	Production of electricity	4011	Production of electricity
4221	Construction of utility projects for fluids	4524	Construction of water projects
4222	Construction of utility projects for electricity and telecommunications	4521	General construction of buildings and civil engineering works
4299	Construction of other civil engineering projects n.e.c.	4525	Other construction work involving special trades
4920	Freight rail transport	6010	Transport via railways
4950	Transport via pipeline	6030	Transport via pipelines
5829	Other software publishing	72	Computer and Related Activities
6110	Wired telecommunications activities	6420	Telecommunications
6120	Wireless telecommunications activities	6420	Telecommunications
6190	Other telecommunications activities	6420	Telecommunications
6201	Computer programming activities	72	Computer and Related Activities
6202	Computer consultancy activities	72	Computer and Related Activities
6203	Computer facilities management activities	72	Computer and Related Activities
6209	Other information technology and computer service activities	72	Computer and Related Activities
6311	Data processing, hosting and related activities	72	Computer and Related Activities
6520	Reinsurance	6600	Aggregate into: Insurance and pension funding, except compulsory social security
6629	Other activities auxiliary to insurance and pension funding	6720	Activities auxiliary to insurance and pension funding

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SIC07	SIC 2007 industry name	SIC03	SIC 2003 industry name
7112	Engineering activities and related technical consultancy	7420	Aggregate into: Architectural and engineering activities and related technical consultancy
7120	Technical testing and analysis	7430	Technical testing and analysis
7211	Research and experimental development on biotechnology	7310	Research and experimental development on natural sciences and engineering
7219	Other research and experimental development on natural sciences and engineering	7310	Research and experimental development on natural sciences and engineering
7220	Research and experimental development on social sciences and humanities	7320	Research and experimental development on social sciences and humanities
7490	Other professional, scientific and technical activities n.e.c.	7420	Aggregate into: Architectural and engineering activities and related technical consultancy
9104	Botanical and zoological gardens and nature reserve activities	9253	Botanical and zoological gardens and nature reserve activities
9511	Repair of computers and peripheral equipment	72	Computer and Related Activities
9512	Repair of communication equipment	72	Computer and Related Activities

Chapter 3

Skill-Biased Management: Evidence from Manufacturing Firms[1]

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3.1 Introduction

There have been major advances in the measurement and analysis of management practices in recent years. Survey data have established the importance of management practices in explaining differentials in productivity between and within countries and sectors (Bloom and Van Reenen, 2007; Bloom et al., 2014*b*). Recent analysis has estimated that across countries, management explains on average around 30 per cent of the gap in total factor productivity with the United States (Bloom, Sadun and Van Reenen, 2017), and experimental evidence from Indian textile plants has shown that management plays a causal role in this regard (Bloom et al., 2013).[2] However, less is known about why firms adopt different management practices (Bloom et al., 2017*a*). Given that management practices are so important for firm performance, and can be measured and benchmarked across firms, why do we not see all firms adopting "best practice"? This paper explores the hypothesis that the local supply of skilled labour shapes the quality of a firm's management practices because it determines the quality of its workforce, including its managers.

Motivated by previously documented associations between management practices and firm skills (see for example, Bloom and Van Reenen (2007) and Bloom et al. (2014*b*)), this paper uses data from the World Management Survey (WMS) to explore the relationship between management practices and measures of local skill availability. We construct a new dataset across 19 countries related to region-level skill availability, and find robust evidence that firms facing more abundant (and hence cheaper) skills have higher management scores (which we refer to as "better managed"), ceteris paribus. This supports the hypothesis that modern management practices and a skilled workforce are complementary, consistent with a skilled workforce increasing the marginal benefit or lowering the marginal cost associated with good management practices, so that firms facing a skill-abundant workforce employ more skilled labour and have better management practices in equilibrium. In this sense, good management practices - adopted as a consequence of the channel studied here - are examples of "skill biased management".

Our approach relies on the assumption that labour markets are local in nature (Moretti, 2011). Our first measure of skill supply is the distance to the nearest university for each plant, which we calculate as a drive time using geocoded information on the surveyed

[2] Much of this literature is focused on interviewing middle managers to understand organisational structures and day to day processes within firms. There have also been major advances in the measurement of CEO behaviour (Bandiera et al., 2017). While CEO behaviour and management practices are correlated with each other, they also appear to be independently correlated with firm performance.

plants in across regions in each of the 19 countries, and universities from the World Higher Education Database (WHED, an international listing of higher education institutions). We find a robust relationship between drive time, firm level human capital and management practices: firms closer to universities have more skilled workers and managers, and are on average better managed. Our results are robust to including firm and geographic controls, and country, time and industry fixed effects. We use region fixed effects to control for unobservable characteristics at the subnational level that are related to university presence and the management of firms.

In the absence of an instrument for university location using international data, we cannot rule out the possibility that the results are driven by better managed firms choosing locations close to universities, though we partially address this concern by showing that there is no differential effect for firms which are founded after their nearest university, and by considering within firm variation in the skill premium analysis. We note however, that if our results are driven by better managed firms making such locational decisions, they are still supportive of a complementarity between better management and skills.

We hypothesise that the mechanism through which universities affect firm human capital and management practices is via increasing the supply of skills, and hence reducing the price of skills. We obtain labour force micro data in 13 countries, which allows us to run wage regressions and estimate the wage premium for university graduates at the subnational region level. Two pieces of evidence support our proposed mechanism. First we show that the skill premium is inversely related to regional university presence (universities per million people). This is a new finding that suggests that skill is expensive when it is relatively scarce in a location and cheap when it is abundant. Second, we replace distance to nearest university with the regional skill premium in our regressions and show that firms facing higher skill premia in the region in which they are located employ significantly less skilled workers and are significantly worse managed. Again these results are robust to the inclusion of the full set of firm and geographic controls (though we are unable to include region fixed effects since our skill price varies at that level). We find that these results are stronger when we exclude capital regions, where we expect demand shocks or other unobservables that raise both the skill premium and management practices are more prevalent.[3]

We explore whether our results are heterogeneous by observable firm characteristics,

[3] Moreover, firms in capital cities are more likely to be able to recruit from wider areas due to other attributes of capital cities which are related to higher labour mobility.

noting that the assumption that labour markets are local may depend on firm type. We find that the relationships between management practices and both university distance and regional skill premia are stronger for single-plant firms compared to plants that are part of multinationals or multi-plant domestic firms. This is intuitive, since these types of firms are likely to be less reliant on the local environment when recruiting staff and setting management practices. Larger multinational firms may be able to attract workers from other regions or countries due to their stronger brand, and might also move staff between locations (Choudhury, 2017). Moreover, management practices in such firms might be set centrally at the company headquarters, which may be in a different region or even country. In contrast, in the distance analysis there is no evidence of heterogeneity with respect to observable university characteristics. Moreoever, there is no evidence of heterogeneity by subject mix. In particular, the results are not driven by universities offering business type courses. This suggests that the university effect is more likely to operate via their role as producers of general human capital, rather than as providers of consultancy services or training for local firms which we might expect to be more prevalent in business schools.

This analysis motivates our use of the distance measure as an instrument to estimate the impact of firm level human capital on management practices. While these results should be treated with caution, it is useful to gauge the size of the effect and the direction in which OLS results are likely to be biased. These results imply that a doubling of the degree share in the average firm could lead to a 0.3 standard deviation increase in management practices. This is economically meaningful as it represents over half the difference between the management practices of the average firm in the United States and United Kingdom.

Our main regressions are estimated using surveyed firms as a cross section. A subset of firms in the WMS were re-interviewed during the sample period which allows us to estimate how changes in firm level human capital and skill prices affect management practices (there is not enough variation in the number of universities to use the distance measure in the panel). This is a demanding specification given the relatively short time frame available in the data, but we show that there remains a robust firm level relationship between human capital and management practices, and a negative but less precise relationship between skill premia and management practices.

The focus in this paper is on testing for complementarities by examining whether firms facing cheaper or more access to skills tend to have better management practices. This is referred to as estimating "demand" equations by Brynjolfsson and Milgrom (2013). We next turn to examine whether there is evidence that a skilled workforce is associated with good management practices because skill increases the marginal benefit of their adoption. Skill biased management would imply that the returns from management practices are higher in the presence of skilled workers. This can be tested using interactions between measures of skills and management practices in "performance equations" (Brynjolfsson and Milgrom, 2013). Financial data are available for a reduced sample of plants, and we estimate simple production functions including distance to university and its interaction with management on this sample. We find that the association between management practices and productivity is lower for plants that are further away from universities, but results are only significant for the sub-sample of single-plant firms, consistent with the finding that locational measures of skill supply appear more important for single-plant firms.

A complementarity between worker skills and management practices may seem intuitive. The surveyed management practices closely resemble the complementary characteristics of "modern manufacturing" discussed by Milgrom and Roberts (1990) and Roberts (1995). Highly skilled, cross trained workers are listed alongside (among other things) lean production techniques, performance tracking and communications as features of the modern firm (Roberts, 1995). A more educated workforce is more likely to show initiative and be able to effectively implement complex, flexible and more decentralised production practices. On the other hand, one could also argue that certain management practices and skilled workers could be substitutes. In the presence of a highly skilled workforce, there may be less need for constant performance tracking and communicating - more able workers could just be left to get on with their jobs. Of course, there may be heterogeneity in these relationships for different types of management practices but our results show that skills and management are, on average, not substitute inputs to production. Shedding light on this issue empirically is therefore valuable for helping managers and policy makers understand best how to improve management practices and hence productivity.

This paper links to four main literatures. First, in the use of the WMS to try to understand differences in management practices, this paper draws on the papers by Bloom, Sadun, Van Reenen and co-authors (for example, Bloom and Van Reenen (2007, 2010); Bloom et al. (2014*b*)). They have shown that education of both managers and workers are strongly correlated with management scores. Using Census Bureau survey data on plants in the US, Bloom et al. (2017*a*) show that plants within counties with "quasi-random" land grant colleges (Moretti, 2004*a*) have significantly higher management scores, and the same can be said for counties with a higher college share in the working age population.[4] Bender et al. (2016) use matched employer-employee data in Germany to show that better managed firms recruit and retain skilled workers.[5] We contribute to this literature by using newly collated international measures of skills which are external to the firm.

Second, we contribute to the evidence on organisational complementarities and skill biased technology. A theoretical framework for thinking about organisational complementarities is set out by Milgrom and Roberts (1990). Brynjolfsson and Milgrom (2013) gives an overview of the theory and empirics of organisational complementarities.[6] Much of the empirical literature has focused on testing whether different types of organisational practices are optimally implemented together (for example Ichniowski, Shaw and Prennushi (1997), Bresnahan, Brynjolfsson and Hitt (2002), or Black and Lynch (2001, 2004)). Our work using regional skill premia uses a similar approach to Caroli and Van Reenen (2001) who find evidence of skill-biased "organisational change". There is compelling evidence that management can be thought of as an organisational "technology" (Bloom, Sadun and Van Reenen, 2017), creating a link to the skill-biased technical change literature. In models of endogenous technology adoption (Basu and Weil (1998), Zeira (1998), Caselli (1999) and tested using time series data in Beaudry and Green (2003, 2005)), when a major technology becomes available, it is not adopted immediately by all agents. Instead it is adopted in environments where complementary factors plentiful and cheap. Beaudry, Doms and Lewis (2010) find that US cities with low skill premia adopted computers more intensively, and Garicano and Heaton (2010) find evidence of complementarity between IT and skilled workers in US police departments. Our core argument is that managerial technology will be adopted in environments where skills are abundant.

Third, our empirical strategy of using distance to universities has been used widely in the labour economics and innovation literatures. Inspired by Card (1995), a number

[4] Together with human capital, this paper explores three other drivers of management practices - competition, business environment and learning spillovers - and finds that together they account for about a third of the variation in management practices.

[5] Using administrative data from Portugal Queiro (2016) finds that firms with educated managers have better performance, and suggests that the mechanism for this involves educated managers being more likely to introduce new technologies.

[6] Ennen and Richter (2010) also give review of the management, economics and other related literatures.

of labour papers have used distance to universities as an instrument for individual level enrollment at university. Distance to universities has also been shown to matter for innovation spillovers.[7] Hausman (2017) analyses the impacts of increases in university patenting on local firms, and finds that establishments technologically or geographically closer to universities experience larger increases in employment and wages. This paper is the first, to our knowledge, that relates distance to universities to firm management.[8]

Finally, and more generally, our paper links to the literature on the regional productivity effects of human capital. Moretti (2004*a*) identifies that the graduates in a regional labour force give rise to spillovers via high wages for other graduates and non-graduates. Gennaioli et al. (2013) highlight the importance of human capital in regional development, and the likely presence of spillovers: in firm level regressions that include firm human capital, regional human capital is also positively related to productivity (see also Moretti (2004*b*)). One mechanism through which this may be operating could be management. Complementarity between skills and management practices would imply that coupled with modern management practices, human capital raises productivity over and above its direct effect on the worker's own productivity. Analyses of regional growth highlight the importance of human capital (Gennaioli et al., 2014) and universities themselves (Valero and Van Reenen, 2018).

3.2 Theoretical Framework

Central to the skill biased management hypothesis is the notion that human capital and modern management practices are complements. In the context of organisational features, these types of idea were developed by Milgrom and Roberts (1990) and Roberts (1995) who analysed "modern manufacturing" and argued that, given that there are complementarities among organisational practices, a range of practices may need to be implemented together for a particular technological advance to raise efficiency. A highly skilled workforce with transferrable skills is listed as one of the features of modern manufacturing.

The management practices scores in the WMS closely resemble Roberts' modern manufacturing. A well-managed firm is defined as one that has successfully implemented

[7] See for example Anselin, Varga and Acs (1997), Henderson, Jaffe and Trajtenberg (1998) and Belenzon and Schankerman (2013).

[8] Using the WHED data on universities, Bloom et al. (2017*b*) show that hospitals closer to universities with both business and medical schools are better managed.

modern manufacturing techniques; and one that is "continuously monitoring and trying to improve its processes, setting comprehensive and stretching targets, and promoting high-performing employees and fixing (by training or exit) underperforming employees" (Bloom et al., 2012).

A simple model helps illustrate one path to our empirical strategy. We assume a neoclassical production function in a static environment. $Y = F(A, M, H)$ where output Y is some function of technology and human capital inputs H with $\partial Y/\partial H > 0$ and $\partial Y^2/\partial H^2 < 0$.[9] We distinguish between production technology A and management technology M (Lucas, 1978). It is assumed that performance is increasing continuously in the level of management quality[10], so $\partial Y/\partial M > 0$ and $\partial Y^2/\partial M^2 < 0$. We model the human capital-management complementarity which we call "skill biased management", $\partial Y^2/\partial M \partial H > 0$, as:

$$M = G(H, A, \eta) \tag{3.2.1}$$

In a complementarity framework we interpret equation 3.2.1 as a demand equation: demand for managerial technology is increasing in complementary human capital (see, for example Bresnahan, Brynjolfsson and Hitt (2002)), but other interpretations are possible.[11]

This framework captures the fact that conditioning on firm level human capital, there is variation across firms in management practices due to other technologies, information frictions, optimisation errors or other idiosyncratic factors (η). In this simple setup we abstract from modelling A. A dynamic model would treat technology as draws from a known distribution, see for example Hopenhayn (1992) or Melitz (2003). We also abstract from entry and exit decisions by assuming that A is large enough to cover fixed costs.

3.3 Empirical Strategy

The simple model forms the basis of an empirical strategy for estimating the effects of human capital on management practices. Suppose we estimated the following using OLS:

$$M_i = \beta_0 + \beta_1 H_i + u_i \tag{3.3.1}$$

[9] We abstract from standard capital and labour for ease of notation.

[10] See Bloom, Sadun and Van Reenen (2017) for a full description of management as a technology, which is modelled as an intangible capital stock, and evidence to support this view.

[11] If we interpret equation 3.2.1 as a production function, better management is "produced" by higher skilled managers or workers. An alternative interpretation (Nelson and Phelps, 1966) is that managers and workers of higher skill are able to draw and adapt random management technology from a better distribution. An interpretation closer to Lucas (1978) is that skilled managers are matched with better workers.

Where for firm i, M is the management score and H is the level of human capital and u is an idiosyncratic error term. Depending on the nature of the omitted technologies A, the bias in OLS estimates could be positive or negative. For example, if information technologies that facilitate better management practices are positively correlated with skills, the bias would be positive. But if communication technologies that facilitate better management practices lead to a reduction in worker skills, the bias would be negative.[12] Intangible assets such as brand or firm culture may also be embodied in this unobserved technology, and such assets are also likely to be correlated with both management practices and worker skills. Moreover, observed correlations between management practices and skills might reflect reverse causality, if workers with higher human capital choose to work in better managed firms. We therefore need to find exogenous variation in workforce skills to be able to make a causal claim about the relationship between skills and management practices.

Our identification strategy uses variation in the skill environments faced by firms, in a world with frictions that prevent the skill price equalising across space.[13] It can be described schematically as follows:

$$Universities_k \rightarrow Skill\ Supply_k \rightarrow Skill\ Price_k \rightarrow H_{ik} \rightarrow\ M_{ik}$$

The first arrow represents the relationship between the spatial presence of universities and supply of human capital (measured as the share of the workforce with a degree in a region k), which we hypothesise will be positive. This rests on the assumption that student mobility is imperfect after graduation, so that at least some graduates stay and contribute to the local labour market. This seems reasonable based on observations in the US and the UK.[14] The share of skilled labour in the region can be expected to affect the relative skill price (or "skill premium"), which we hypothesise will affect the hiring decisions of firms. All else equal, we would expect that a higher skill premium would result in a lower degree share in the firm (H_{ik}) since skilled labour is more expensive relative to unskilled labour.

[12] Bloom et al. (2014*a*) find that improvements in information technologies lead to decentralisation, while improvements in communication technologies have the opposite effect.

[13] In the absence of frictions, the price of skill would equalise (via the law of one price). In such a world, university presence should have no effect on skill shares in a local area. In reality, frictions and the inelastic supply of non-tradables such as land limit the extent of price equalisation - see for example, Roback (1988) and Glaeser and Gottlieb (2009).

[14] For example, Kodrzycki (2001) looks at NSLY data in the US and finds that over two-thirds of college graduates remain in the same state post graduation. Data from the UK Higher Education Statistics Authority shows that a high fraction of first degree graduates in a region remain in the same region for work. In 2004-05, this fraction was 61 per cent.

Finally, skill biased management would imply that there is a positive relationship between firm level human capital and the adoption of complementary management practices.

Our empirical approach to estimating these relationships is largely dictated by data availability and issues of aggregation. We begin with the reduced form relationship between university presence and firm skills and management practices ($Universities_{ik} \rightarrow H_{ik}, M_{ik}$), calculating a firm specific distance measure between each firm and its closest university. In this analysis we are able to examine within region variation, so that unobservable factors that affect regional skills and firm outcomes are controlled for. To get more information on the mechanism and explore the effects of relative skill prices, we aggregate to the region level (equivalent to a US state). We explore the associations between regional skill prices, firm skills and management practices ($Skill\ Price_k \rightarrow H_{ik}, M_{ik}$), and link university presence in a region with regional skills and prices ($Universities_k \rightarrow Skill\ Supply_k, Skill\ Price_k$). Finally, we use distance to closest university as an instrument to estimate the relationship between firm skills and management practices ($Universities_{ik} \rightarrow H_{ik} \rightarrow M_{ik}$), this piece of analysis allows us to understand better the likely bias in the OLS regressions of management practices on firm-level human capital. Our empirical specifications are outlined in more detail in the next section.

3.3.1 Distance to University, Firm Skills and Management Practices

Our reduced form analysis examines the relationships between firm skills and management practices and distance to closest university. We estimate:

$$Y_{ijkct} = \alpha_1 Dist_{ijkct} + X'_{ijkct}\alpha_2 + \phi_j + \xi_k + \tau_t + \varepsilon_{ijkct} \tag{3.3.2}$$

We observe firm i in sector j, region k, country c and survey year t. The outcome variable $Y \in \{M, H\}$. The distance variable, $Dist$, is measured as the drive time to the nearest university in hours. We expect α_1 to be negative, firms closer to universities should have a higher degree share and be better managed, due to their improved access to skills.

We include a number of firm controls (X) that have been shown to matter for management practices (see for example Bloom and Van Reenen (2007); Bloom, Sadun and Van Reenen (2017)), and are likely to be related to skill share in the firm too (such as size, age and ownership status - we also include industry fixed effects ϕ_j). To pick up any differences over the years in which the WMS surveys are conducted, we include year dummies τ_t. ε_{ijkct} is the error term, which we cluster at the region level to allow for heteroskedasticity and correlation between firms in the same region.

To address concerns regarding location specific factors which may confound our estimates we do several things. First, we include regional fixed effects (ξ_k). We also control for geographic characteristics which may be correlated with both skills and the management of firms: in particular population density within 100km of the plant (also, longitude and latitude).

There are two main concerns around this estimation strategy. First, we may worry that well managed firms are endogenously located close to universities. To partially address this we examine universities founded after the firms were founded and show our results are similar. It seems less likely that there would be issues of reverse causality (that universities choose locations close to medium sized manufacturing firms - those surveyed in the WMS - with higher management scores), or firms endogenously choosing locations on the basis of future university openings.

Second, we may worry about the interpretation of a relationship between distance to universities and management practices. Such a relationship could be due to the diffusion of information or advice from universities to surrounding firms, for example via consultancy services, managerial training or access to more specialised inputs - rather than through an effect on the supply of skills as our diagram suggests. If this were the case, we would expect that universities with certain subject mixes may have more of an effect - in particular, business, economics, finance, or even engineering and sciences. We are able to filter such universities, and show that they do not drive our results.

Under the caveats above and the (strong) assumption that the exclusion restriction holds, i.e. that universities affect management only via their impact on the supply of skills, we estimate the relationship between firm skills and management using the distance measure as an instrument for firm skills. This allows us to assess the likely direction of bias in the OLS relationship, and gain a better understanding of the order of magnitude of the relationship between firm skills and management.

3.3.2 Regional Skill Premia, Firm Skills and Management Practices

We now turn to our analysis of how firm human capital and management practices respond to the relative price of skills they face. The purpose of this part of the analysis is to provide evidence that firms respond to regional skill prices and show that those skill prices appear to be related to university presence in a region.

Skill premia (the log ratio of skilled wages to unskilled wages) need to be calculated based on some type of locational unit - and in line with the literature (for example Caroli and Van Reenen (2001) or Gennaioli et al. (2013)) and what is feasible from a data perspective (see next section) we choose the subnational region, equivalent to a US state.

The estimating equation is as follows:

$$Y_{ijkct} = \gamma_1 SP_k + X'_{ijkct}\gamma_2 + \phi_j + \zeta_c + \tau_t + v_{ijkct} \tag{3.3.3}$$

SP_k is the average skill premium (most commonly defined as the log ratio of average skilled and unskilled wages) for region k over the period 2005-2010. Our main measure is the coefficient on a degree dummy from wage regressions, which is an estimate of the skill premium having controlled for other factors (such as worker experience). The controls (X) are consistent with equation 3.3.2. Since the skill premium varies at the regional level, we are unable to include region fixed effects in these regressions, but we do include country dummies (ζ_c), together with sector and year dummies as before (ϕ_j and τ_t). Our coefficient of interest is γ_1, which we expect to be negative: firms facing a higher skill premium will have lower human capital and be worse managed if skill biased management holds.

These regressions are weighted using the population in a region divided by the population in the country to reduce the effects of outliers in low population regions (for which labour force data is likely to be less reliable), and standard errors are clustered at the region level as before.

3.4 Data

3.4.1 Overview of Data Sources

We use data from three main sources. Here we describe the key features of the data, and further details are in the Data Appendix 3.A. Survey data on management practices and skills in manufacturing plants are obtained from the World Management Survey (WMS). The unit of observation is the manufacturing plant (referred to interchangeably as the firm in this paper). The WMS specifically asks questions about the management practices in the particular plant surveyed (rather than the head office, which might differ in the case of multi-plant firms). Therefore the WMS gives a measure of managerial quality at a particular location, implying that the spatial approach taken in this paper is appropriate. The measure of management practices is the standardised WMS management score, which is based on the average score that a plant achieves across 18 practices (broadly relating to operations, monitoring, targets and people management) (see Appendix Table 3.D.7). It has been shown that management scores are positively and robustly correlated with performance (Bloom and Van Reenen, 2007; Bloom et al., 2014*b*; Bloom, Sadun and Van Reenen, 2017), a relationship that holds across countries, sectors and types of firm. We therefore interpret a higher management score as "better" management. The share of the workforce with a university degree is our measure of human capital - this is available for the total workforce, and managers/non-managers separately. In the distance analysis, we use data from surveys conducted between 2004 and 2010 across 19 countries, as a pooled cross section.

Information on universities across countries is sourced from the World Higher Education Database (WHED), which provides data on the location and other university characteristics (such as subjects or level of study offered, and founding date). See Valero and Van Reenen (2018) for a full description of the data. We geocode universities and plants, by mapping their postcodes to geographic coordinates. This enables us to calculate the main distance measure by estimating drive times between each plant and its nearest university (based on google maps). We favour drive time instead of a straight line distance because it accounts for natural geographic features. Given that the analysis in this paper is based on an international sample with differing geographies across countries, this helps to account for distance in a consistent manner. Alternative distance measures are explored in the robustness.

Analysis of the relationships between regional skill premia, firm human capital and management practices is conducted on a subsample of 13 countries where we were able to access international labour force survey (or equivalent) data sources (for more details on the data sources see Table 3.D.9 in the Appendix). Skill premia are estimated using wage regressions, where log wages are regressed on education, experience, experience squared and gender, by region. Instead of the standard years of education, our preferred specification includes a dummy variable to indicate whether or not an individual has a degree, and the estimated skill premium is the coefficient on this dummy. Available observations in regions are pooled over the years data were available, and year fixed effects included in the regressions. We also compute the regional degree share and a raw wage ratio (the log ratio of skilled wages to unskilled wages), measures that were available for additional countries as ready-made regional aggregates.[15]

The key geographic control is population density at the location of the plant (within 100km), which is based on data from the Center for International Earth Science (CIESIN) data. Other regional data were obtained from Gennaioli et al. (2013). In addition to average years of education, and college share which is used to sense check the supply of skills data collected from surveys, there are also other covariates such as as temperature, inverse distance to coast and oil per capita and population.

3.4.2 Descriptive Statistics

A summary of the key variables used in our analysis is at Table 3.4.1. The mean management score in our sample is just under 3. In the average plant, 15 per cent of the total workforce in the average plant have a degree. This is closer to 60 per cent looking only at managers, and 10 per cent for non-managers. In our regressions we take the natural log of the degree share, and add one so that zero observations are kept in the sample. We control for plant and firm employment, plant age and MNE status.[16] Just under half of plants are part of a multinational enterprise, and 59 per cent have more than one production site (multi-unit production). In our analysis, we consider multi-plant firms those that are either part of a multinational, or have multi-unit domestic production. 50 per cent of the plants are part of a large firm (which we define as having over 300 employees), and 28 per cent are listed. 40 per cent of the workforce of the average plant is in a union.

The average distance (drive time) to the nearest university is 0.45 hours. Figure 3.4.1 plots the histogram of driving times in 10 minute bins which is clearly skewed to the right. In the robustness, we experiment with using the natural log of the drive time, and exclude observations that are in the same postcode as universities (and hence have a drive time of zero). Locational features are controlled for by including longitude, latitude and average population density within a 100km radius of the plant. The average plant in our sample is in a region where the skill premium is 0.57, 19 per cent of the workforce have a degree and there are 3.66 universities per million people.

Country-level descriptive statistics on the sample on which we conduct our analysis are reported in Appendix Table 3.D.1. The United States has the highest management scores on average, though there is also substantial within-country variation. The highest

[15] Microdata were obtained for 14 countries, and ready-made regional aggregates for an additional 4 countries. Our main analysis sample is based on 13 countries where reliable wage data were available, and the wider samples are included in robustness.

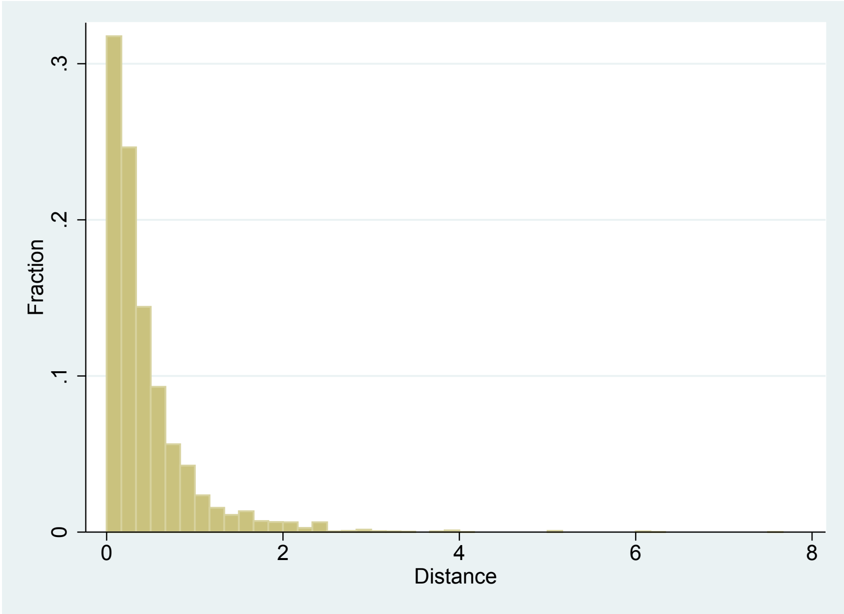
[16] Missing values are imputed and a dummy to indicate missing status is included in regressions.

Table 3.4.1: Descriptive Statistics

	Mean	S.D	Min	Max	Count
WMS variables					
Management Score	2.93	0.67	1	4.89	6363
Management Z-Score	0	1.00	-2.89	2.94	6363
Degree share	14.8	16.7	0	100	6363
Degree share, managers	58.2	34.0	0	100	6363
Degree share, non managers	10.4	16.3	0	100	6363
Ln(1+degree share)	2.25	1.05	0	4.62	6363
Ln(employment, plant)	5.10	0.96	0	8.99	6363
Missing Ln(employment, plant)	0.017	0.13	0	1	6363
Ln(employment, firm)	5.83	1.11	0	11.1	6363
Missing Ln(employment, firm)	0.0016	0.040	0	1	6363
Ln(plant age)	3.40	0.79	0	6.28	6363
Missing Ln(plant age)	0.44	0.50	0	1	6363
MNE	0.46	0.50	0	1	6363
Multi-unit production	0.59	0.49	0	1	6363
Large Firm (>300 employees)	0.50	0.50	0	1	6363
Public listed	0.28	0.45	0	1	6363
Union (percent)	39.8	39.4	0	100	6363
Google Maps and GIS variables					
Distance	0.45	0.54	0	7.55	6363
Latitude	23.3	32.7	-54.8	65.7	6363
Longitude	8.01	78.1	-127.5	176.9	6363
Avg pop density	1.34	1.88	0	16.0	6363
Regional skills variables					
Skill Premium	0.57	0.22	0.26	1.25	4559
Regional Degree Share	18.6	8.01	0.11	52.7	6189
Universities per million people	3.66	3.74	0	129.7	6363

NOTES: *Management score* is the average of all 18 WMS management scores. *Management Z-score* is the standardised score. *Degree share*, *degree share (managers)* and *degree share (non managers)* are the plant-level percentages of total workforce, managers and non-managers with degrees, respectively. *Ln(1+degree share)* is the natural log of 1+ the total workforce degree share. Missing values of firm, plant employment and plant age are mean coded and an indicator shown. *Union* is the percentage of the workforce that is unionised. *Distance* is the google driving time in hours from the plant to the nearest university (full description in the Data Appendix). *Longitude* and *Latitude* are geographic coordinates of the plant location corresponding to its postal code. *Avg pop density* is the average population density within a 100km radius of the plant calculated using GIS software. *Skill premium* is the coefficient on a degree dummy, recovered from regional wage regressions. *Regional degree share* is the percentage of regional population with a degree. *Universities per million people* is the number of universities in a region, divided by the population. Appendix Table 3.D.2 summarises additional variables used in our analysis and robustness checks.

Figure 3.4.1: Histogram of Distance Measure



NOTES: N=6,363, observations split into 10 minute bins. Distance is measured as the drive time (in hours) between a plant and its nearest university.

degree share is in Japan, where 32 per cent of the workforce of the average plant are university graduates. The skill premia appear of reasonable magnitude compared to estimates from the literature.[17] There is also variation in the mean distances and skill premia across countries.

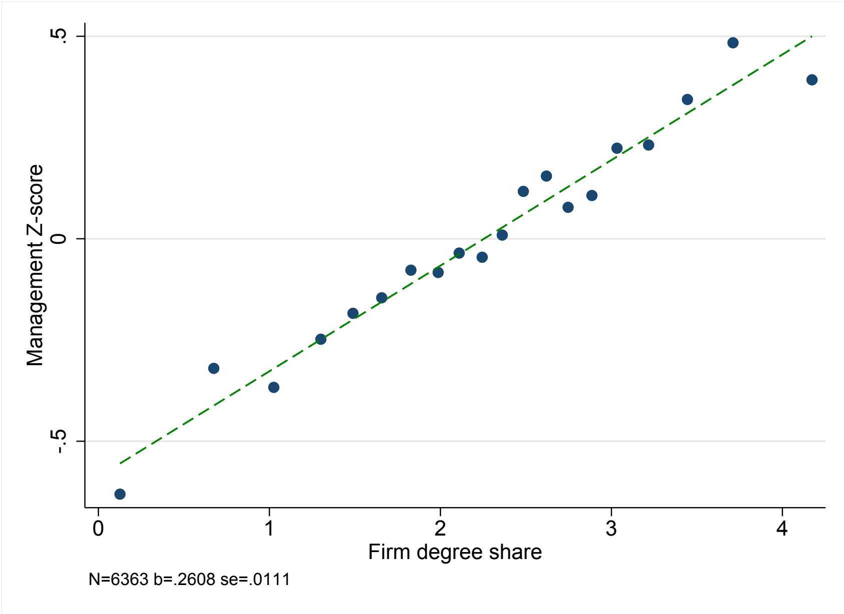
In this paper our focus is on finer grained analysis based on variation within countries or regions. The region in this analysis is equivalent to a US state or NUTS1 or NUTS2 regions in Europe, and our sample contains 314 such regions across the 19 countries listed. In the Appendix we report the number of regions in each country and show that there is substantial within-region variation (Table 3.D.3).

Before moving on to our results, we report some raw correlations that motivate the analysis. The firm level correlation between degree share and management practices has been established in the literature (see Bloom and Van Reenen (2007), Bloom et al. (2014*b*), and with more detail on Germany in Bender et al. (2016)), and is the starting point for this study. Figure 3.4.2 plots the correlation between average management scores of firms within 20 equally sized bins in terms of degree share, showing a positive and precise relationship.[18] This graph includes country fixed effects, but the relationship is as strong

[17] For example, see Strauss and de la Maisonneuve (2007) for OECD country estimates.

[18] These relationships are as strong using the unlogged degree share, but we use the natural log since this provides a better fit to the data (the equivalent plot of the unlogged degree share reveals a non-linearity in the relationship).

Figure 3.4.2: Firm skills and management practices



NOTES: Scatter plot of average firm management practices on average ln(1+degree share) within 20 evenly sized bins. Variation is within country. The solid line represents the line of best fit.

without these.

This strong relationship exists for both managers and non managers as shown in Table 3.4.2 which reports the regression equivalent.[19] A Wald test on the coefficients on managers and workers in column (4) shows that these are not significantly different from each other, and we keep our focus on total workforce skills in the analysis that will follow.

Table 3.4.2: Firm Skills and Management Practices, Basic Regressions

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)
Ln(1+degree share)	0.262***			
	(0.015)			
Ln(1+degree share), managers		0.207***		0.138***
		(0.013)		(0.011)
Ln(1+degree share), non managers			0.198***	0.156***
			(0.010)	(0.010)
Observations	6,363	6,363	6,363	6,363

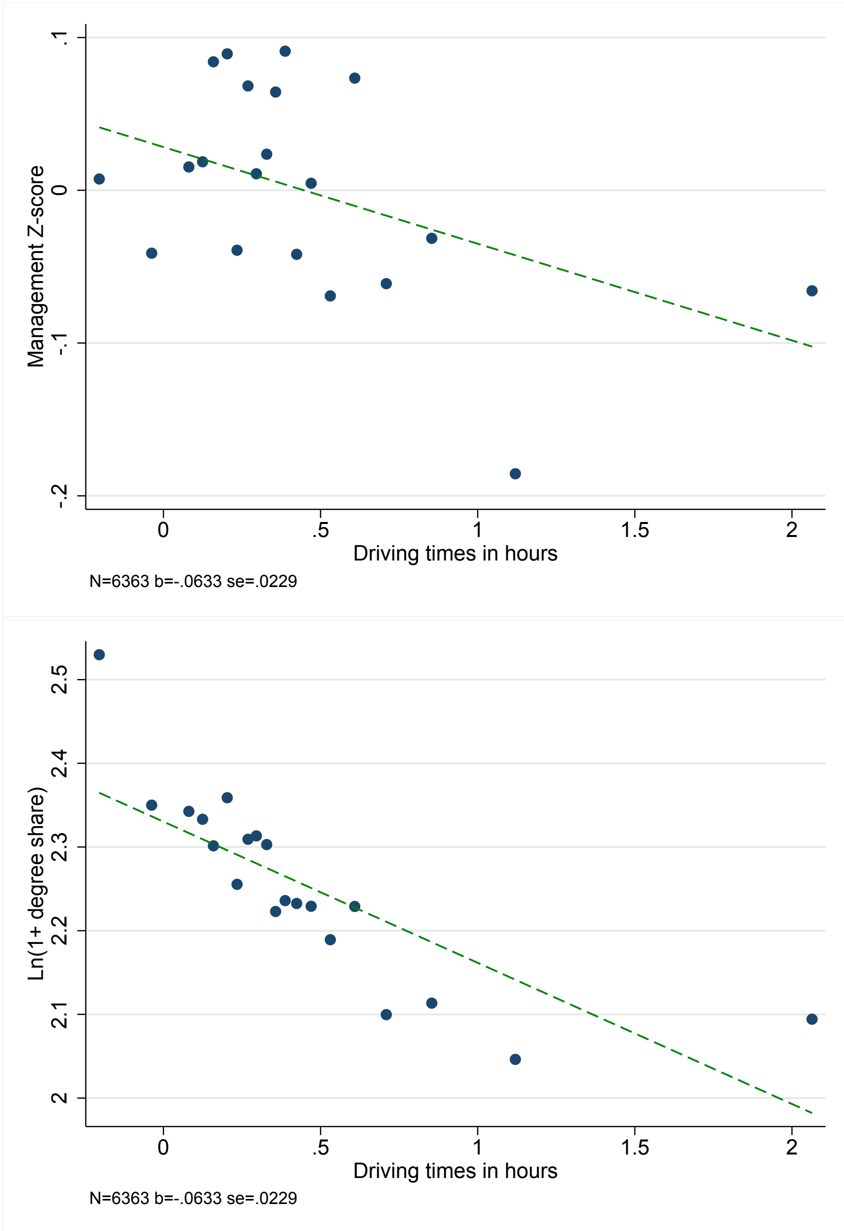
NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses (for consistency with later analysis). All columns include country and year dummies.

Figure 3.4.3 allows us to visualise our analysis using distance to universities, now

[19] The relationship between firm skills and management practices remains highly significant and of similar order of magnitude when a full set of controls are included, as can be seen in column (2) of Table 3.5.5.

plotting average management scores within 20 equally sized bins. This shows that there is a negative correlation between our distance measure and both management scores and the firm level degree share.

Figure 3.4.3: Distance to University, Management Scores and Degree Share



NOTES: Scatter plot of average management Z-score on average travel time within 20 evenly sized bins. Variation is within country. The solid line represents the line of best fit.

Finally, we examine the relationships between skill prices and regional degree share. A key assumption in our regional skill premium analysis is that a higher price of skills in a region reflects lower supply and we therefore expect a negative correlation. We find that this is the case, (see Appendix Figure 3.C.1), and that the correlation is stronger when we omit capital regions. This seems intuitive, as demand shocks and other unobservables that raise both the skill premium and the supply of skilled workers may be considered more likely in hubs of economic activity.[20]

3.5 Results

3.5.1 Distance to University, Firm Skills and Management Practices

We begin with our analysis of the reduced from relationships between firm management practices, degree share and distance to university (Table 3.5.1). The dependent variable in Panel A is the standardised management score. Column (1) is a simple correlation, country and year dummies plus survey controls to reduce noise in the data. The relationship between management scores and distance is negative and significant. Column (2) adds region fixed effects which have little impact on the main coefficient. In column (3), industry dummies and firm controls (as reported) are added and these reduce the magnitude of the coefficient slightly to -0.05. Column (4) adds geographic controls (population density, longitude and latitude, not reported here) none of which are significant, and the our coefficient is unchanged. Column (4) is the core specification, and implies that plants that are an extra hour of drive time away from their closest university (which is roughly two standard deviations) have on average 0.05 standard deviations worse management practices. In the next section we show that this result is robust to alternative specifications and sample selection.

Panel B reports regressions of firm level degree share on distance to university. Again, there is a significant and negative correlation between distance and degree share of -0.16 (column (1)). This decreases slightly in magnitude as we add controls in the order discussed previously. The result in column (4) implies that an extra hour of driving time reduces the log degree share by 0.12, representing over a tenth of the standard deviation across firms.[21]

This analysis suggests that, within regions, firms located close to universities have both higher human capital and higher management scores. In the following sections we will provide evidence to suggest that the mechanisms underlying this is, at least in part, the role of universities in increasing the supply of skills in their local area. While we

[20] To reflect this, our regional regressions that follow include a dummy variable indicating regions that contain a capital city.

[21] We also estimated column (4) for managers and non-managers separately and found that the effect is negative and highly significant for both (the coefficient on distance for degree share of managers is -0.087, and the coefficient for non managers is -0.12, both are significant at the 1 per cent level).

Table 3.5.1: Distance to University, Plant Management and Skills

	(1)	(2)	(3)	(4)
A: Dependent variable is Management Z-score				
Distance	-0.067***	-0.070***	-0.049***	-0.050***
	(0.018)	(0.019)	(0.018)	(0.019)
Ln(employment, plant)			0.200***	0.199***
			(0.017)	(0.017)
Ln(employment, firm)			0.073***	0.073***
			(0.012)	(0.012)
Ln(plant age)			-0.029**	-0.029**
			(0.014)	(0.014)
MNE			0.389***	0.389***
			(0.031)	(0.031)
B: Dependent variable is Ln(1+Degree Share)				
Distance	-0.160***	-0.144***	-0.114***	-0.119***
	(0.029)	(0.029)	(0.027)	(0.027)
Ln(employment, plant)			0.060***	0.059***
			(0.019)	(0.019)
Ln(employment, firm)			0.020	0.020
			(0.017)	(0.017)
Ln(plant age)			-0.015	-0.015
			(0.018)	(0.018)
MNE			0.234***	0.234***
			(0.032)	(0.032)
Observations	6,363	6,363	6,363	6,363
Number of clusters	314	314	314	314
Region dummies	no	yes	yes	yes
Industry dummies	no	no	yes	yes
Geography controls	no	no	no	yes

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. See Table 3.4.1 for a description of the key variables. All columns include country dummies, year dummies, and survey controls for interviewer gender, interviewee job tenure, interviewee seniority, interview reliability, interview day of week, time and duration, and dummy variables for the analyst conducting the interview. Missing values are mean-coded, and dummies included to indicate where this is the case. Geography controls include population density, longitude and latitude.

cannot rule out the possibility that better managed firms are locating near to universities, or universities are providing other support that raises management practices with these data, we go some way towards addressing these concerns.

3.5.2 Regional Skill Premia, Firm Skills and Management Practices

We begin the regional analysis with simple correlations linking the university location to regional skill premia (Table 3.5.2). Unsurprisingly, we find that there is a direct relationship between a universities per million people and measures of skill supply: regional degree share (Panel A) and the skill premium (Panel B). Column (1) includes only country dummies, and shows that there is a positive correlation between university density and the logged regional degree share, significant at the 5 per cent level. This suggests that a one per cent rise in university density is associated with a 15 per cent rise in degree share. Controlling for observable geographic characteristics at the regional level (temperature, distance to the coast, oil and gas production, population, and a capital region dummy) actually increases precision, and does not affect the size of the coefficient (column (2)). As we expect, we see a negative correlation between university density and the skill premium, though this is less precise (Panel B).

Table 3.5.2: Regional Skills and Universities

	(1)	(2)
A: Dependent variable is Ln(region degree share)		
Ln(1+universities per million people)	0.153**	0.147***
	(0.069)	(0.044)
B: Dependent variable is skill premium		
Ln(1+universities per million people)	-0.030*	-0.030*
	(0.015)	(0.014)
Observations	208	208
Country dummies	yes	yes
Geographic controls	no	yes

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the country level in parentheses. All columns contain country dummies. The unit of observation is a region. Geographic controls include a capital region dummy, temperature, inverse distance to the coast, Ln(oil production) and Ln(population).

Next we summarise the relationships between regional skill premia, and firm management practices and human capital (Table 3.5.3).

The dependent variable in Panel A is the standardised management score. Column (1) reports a simple correlation (controlling for country and year fixed effects) showing that management scores are negatively and significantly related to regional skill premia. Column (2) adds 2 digit industry dummies which slightly reduces the coefficient and firm controls (consistent with our previous analysis) which reduces our coefficient. The addition of plant level geographic controls (longitude, latitude and population density) in column (3) increases significance.[22] Column (4) adds survey controls and our coefficient is slightly reduced.[23] The coefficient of -0.74 implies that a one per cent rise in the degree premium leads to a 0.0074 standard deviation reduction in management scores. To assess the magnitude of this effect, we apply it to the variation between US states. It implies that a one standard deviation rise in the skill premium reduces management scores by -0.04 standard deviations, representing 15 per cent of the cross-state variation.[24] Column (5) reports the result when capital regions are dropped, the relationship is now stronger and significant at the 1 per cent level, suggesting that unobservables that raise management practices and also raise the skill premium are more prevalent in capital regions.

The relationship between skill premia and degree share is less precisely estimated (Panel B), but still negative. In fact our coefficient gets stronger and more precise as geographic controls are added, in particular the capital region dummy. In column (4), the coefficient is -0.821, and significant at the 5 per cent level. As in Panel (A), excluding capital regions altogether increases the magnitude of the effect and its significance.

3.5.3 Robustness and Heterogeneity of Main Results

3.5.3.1 Summary of Robustness Tests

The results so far provide strong evidence that distance to university and regional skill premia matter for firm management practices. We test the robustness of the relationships between management practices and both the distance and skill premium measures, and the results are detailed in Appendix 3.B. First, we show that the distance results are robust

[22] We show that the core specification, column (4) is robust also to the addition of regional geographic controls in the robustness (see Appendix Table 3.D.11, row (8)).

[23] Here we exclude the analyst dummies. This model using region-level variation has fewer effective degrees of freedom and we find that the analyst dummies have a large effect, reducing the magnitude of the coefficient and raising the standard errors (see robustness tests in Appendix Table 3.D.11). We therefore leave them out of this core specification.

[24] The cross-state standard deviation of the degree premium in the US is 0.058. -0.7 x 0.058 = -0.04, which is 15 per cent of the cross region standard deviation in management scores (0.28).

Table 3.5.3: Regional Skill Premia, Plant Management and Skills

	(1)	(2)	(3)	(4)	(5)
A: Dependent variable is Management Z-score					
Skill Premium	-1.028**	-0.668*	-0.802**	-0.737**	-0.925***
	(0.481)	(0.371)	(0.363)	(0.349)	(0.258)
Ln(employment, plant)		0.274***	0.274***	0.240***	0.254***
		(0.029)	(0.030)	(0.028)	(0.032)
Ln(employment, firm)		0.081***	0.082***	0.062***	0.053***
		(0.017)	(0.016)	(0.017)	(0.020)
Ln(plant age)		-0.025	-0.026	-0.037*	-0.031*
		(0.019)	(0.018)	(0.021)	(0.018)
MNE		0.521***	0.516***	0.467***	0.388***
		(0.051)	(0.051)	(0.050)	(0.050)
capital			0.060	0.061	
			(0.054)	(0.048)	
B: Dependent variable is Ln(1+Degree Share)					
Skill Premium	-0.648	-0.576	-0.786**	-0.821**	-0.914***
	(0.493)	(0.400)	(0.351)	(0.340)	(0.282)
Ln(employment, plant)		0.077**	0.079**	0.074**	0.062***
		(0.034)	(0.035)	(0.036)	(0.023)
Ln(employment, firm)		0.016	0.017	0.011	0.018
		(0.020)	(0.020)	(0.019)	(0.020)
Ln(plant age)		-0.000	-0.002	-0.001	0.017
		(0.026)	(0.026)	(0.026)	(0.022)
MNE		0.355***	0.349***	0.337***	0.295***
		(0.045)	(0.046)	(0.047)	(0.048)
capital			0.124**	0.132***	
			(0.049)	(0.047)	
Observations	4,553	4,553	4,553	4,553	3,880
Number of clusters	208	208	208	208	198
Industry dummies	no	yes	yes	yes	yes
Geographic controls	no	no	yes	yes	yes
Survey controls	no	no	no	yes	yes
Capital regions	yes	yes	yes	yes	no

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Regressions are weighted using population in the region as a share of country population. All columns include country and year dummies. Industry dummies are 2 digit SIC code, geography and survey controls as before (but excluding the analyst dummies) (see Table 3.5.1). See Table 3.4.1 for a description of the key variables.

to different specification assumptions with respect to the clustering of standard errors, allowing non linearities in the distance measure, including additional geographic controls (in particular local population density), or more detailed fixed effects. The distance coefficient remains negative and significant on the inclusion of country - year dummies, and region-industry dummies. Significance is lost in some of the more demanding specifications, for example using county or city level fixed effects, but the coefficients are still negative. Results are also robust to different sample choices.

Analogue robustness tests are carried out on our regional skill premium regressions (using the full sample that includes capital regions), These show that the sign of the relationship between skill premia and management practices is robust to different assumptions on specification and sample, but the significance of these results is lost in some cases. In particular, when standard errors are clustered at the country level, or when the regressions are unweighted (more noise is expected as skill premia are likely to be worse measured in less populous regions where sample sizes are smaller). In addition, we explore whether the expected relationships exist for alternative measures of regional skills such as a raw regional wage ratio or various quantity measures (such as degree share or regional years of education). In general, the coefficients on these measures are as expected but they tend not to be significant. Reassuringly, we find that our regional measure of university presence (universities per million people) has a positive and significant relationship with management practices.

3.5.3.2 Heterogeneity Across Firm or University Type

Next, we explore whether there is heterogeneity in these relationships across observable dimensions. We find evidence of heterogeneity in effects between plants that belong to multi-plant enterprises (defined as either being part of multinational firms or firms that have more than one production site domestically) and those that are single-plant firms. This appears to be the case in both the distance and skill premium specifications (Table 3.5.4). Column (1) shows our distance regression with a dummy for multi-plant firms.[25] In column (2) we add an interaction term between distance and the multi-plant dummy. This is positive but not significant, but the effect for single-plant firms is slightly larger. In columns (3) we replicate column (2) on the sample for which skill premia are available. The average effect across all plants on the reduced sample is similar in this sample (0.056

[25] We vary our previous regressions here slightly by including a multi-plant dummy rather than only the MNE dummy from before.

compared to 0.050 in the full sample), but the effect of distance in single-plant firms is double the size (-0.11), and the interaction term is larger and more significant (the p value is 0.102). Columns (4) and (5) show that similarly the skill premium has a stronger relationship with management practices in single plant firms, now the interaction term is significant at the 5 per cent level.

The finding that regional skill supply has a stronger effect on management practices in single-plant firms is intuitive. Plants that are part of a larger firm are likely to have access to wider labour markets and we therefore might expect recruitment decisions to be less influenced by the local skill environment. It also may well be the case that management practices and processes are set centrally at their headquarters, so are less sensitive to the local skill environment of specific plants.[26]

Table 3.5.4: Heterogeneity by Multi-plant Status

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)	(5)
Distance	-0.050***	-0.058*	-0.109***		
	(0.019)	(0.034)	(0.037)		
Distance X Multi		0.012	0.080		
		(0.043)	(0.049)		
Skill Premium				-0.710*	-1.026**
				(0.376)	(0.399)
Skill Premium X Multi					0.411**
					(0.163)
Multi	0.267***	0.261***	0.280***	0.400***	0.152
	(0.031)	(0.036)	(0.045)	(0.043)	(0.126)
Observations	6,363	6,363	4,553	4,553	4,553
Number of clusters	314	314	208	208	208

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. *Multi* is a dummy denoting multi-plant status, which we define as a plant that either belongs to a multinational enterprise, or a domestic multiplant firm.

Second, we investigate whether specific types of university are driving the distance results. Heterogeneity across universities may tell us something about the mechanism through which universities might impact on local firms. If we find stronger effects for universities with business departments, this could imply that it is the managerial skills that are important for the management of firms rather than general human capital. Furthermore, we might worry that the effects we have found are due to universities

[26] We explore heterogeneity across other firm characteristics, and in general there is no evidence of this in the distance specifications, while the skill premium regressions do display some heterogeneities across other characteristics (for example listed status and larger firms).

providing consulting services or other support to local firms rather than the provision of human capital, and stronger effects universities with business departments could suggest this type of mechanism is at work. The results show that there is no evidence of heterogeneity for universities offering business type courses or any other subject type (law and social sciences, medicine and science or arts and humanities), suggesting that universities affect firm management via their effect on general human capital rather than through the teaching of any particular discipline (see Table 3.D.4 in the Appendix). We also examine whether the university effect is stronger for universities that were founded before the plant. If better managed firms have based location decisions on the proximity to existing universities, then we may expect a stronger coefficient when we look at universities founded before the plant. In fact, we find that there is no differential effect in such cases, therefore, it does not appear better managed plants locating near established universities are driving our results.

Finally, we check whether the relationships between management practices and skills measures that we have found exist for all the types of management practices scored in the WMS, or whether skills are more important for a subset of these. We run our regressions distance and skill premium regressions with the standardised scores for each of the four different management practice groupings as dependent variables: operations, monitoring, targeting and people management. We find that the negative relationship between our both distance and skill premia applies across all practice groupings. This is consistent with the empirical fact that management practices within firm are correlated: a firm that scores highly on one managerial question will tend to score highly on all of them (Bloom et al., 2014*b*). The coefficients vary in significance but not in a consistent manner across the two specifications, so we cannot conclude that these results are driven by a particular subset of management practices (see Appendix Table 3.D.5).

3.5.4 Firm Human Capital and Management Practices

In order to better interpret the endogenous firm level relationship between degree share and management practices and assess the likely sign of bias, we estimate the effect of firm degree share on management practices using distance to nearest university as an instrument for firm level degree share. We treat these results with caution, as they rely not only on the exogeneity of university location, but also on the assumption that universities affect the management of firms only via their impact on firm degree share, rather than through direct consultancy, training services or other externalities. While it is not possible to prove exclusion, we argue that the fact that universities with business departments do not have differential effects helps to address concerns that universities affect management practices through other channels. Similarly, we cannot rule out endogenous university location within regions, though we do show that there is no differential effect where the plant's closest university was founded before the plant itself.

The results of the instrumental variables analysis are summarised in Table 3.5.5. Column (1) gives the correlation between total workforce degree share and management practices, controlling for country and year dummies which we saw in Table 3.4.2. This is robust to the inclusion of the full set of controls (column (2)). Column (3) reports the just identified IV regression, where degree share is instrumented with drive time. The first stage F-statistic is of a large magnitude (19.7) and so we do not appear to have a problem of weak instruments (Staiger and Stock, 1997; Stock, Wright and Yogo, 2012).[27] Column (4) shows the results of using an additional instrument: the number of universities within 100km of the plant, which is of course correlated with drive time but also reflects the presence of other universities in addition to the closest one. The results are very similar to our just identified model.

Table 3.5.5: Firm Degree Share and Management Practices with IV estimates

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)
Specification:	OLS	OLS	IV	IV
Ln(1+degree share)	0.262***	0.156***	0.420***	0.418***
	(0.015)	(0.014)	(0.142)	(0.130)
Observations	6,363	6,363	6,363	6,363
Number of clusters	314	314	314	314
Region dummies	no	yes	yes	yes
Industry dummies	no	yes	yes	yes
Firm controls	no	yes	yes	yes
Geography controls	no	yes	yes	yes
Instruments			Distance	Distance, Unis<100km
F statistic			19.70	16.52

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Standard errors clustered at the region level in parentheses. All columns include country and year dummies.

[27] Note that the first stage is equivalent to specification in Panel B, column (4) from Table 3.5.1.

The IV specification in (3) is robust to a multitude of tests, summarised in Appendix 3.B. We also provide some additional reassurance on exclusion and the exogeneity of university location. To address the concern that universities affect management channels other than human capital we explore whether universities with business departments have a direct effect on management practices (both a main effect and interacted with distance[28]), see Appendix Table 3.D.6. The excluded instrument for firm human capital is now the distance to universities without business departments. Business departments do not appear to have a direct effect on management, and the IV coefficient is of similar magnitude. We carry out an equivalent exercise for universities founded before the plants, where now the excluded instrument is universities founded after the plant; and find no effect of pre-existing universities on management practices which is inconsistent with a view that better managed firms endogenously locate near to universities.

This analysis suggests that OLS estimates are biased downwards.[29] We use the IV coefficient to estimate that if the average firm doubled its degree share, this could imply higher management scores of 0.3 standard deviations:[30] over half the size of the difference between the average UK and US plant (see Appendix Table 3.D.1).

3.5.5 Extensions

3.5.5.1 Panel Estimates: Management Practices and Skill Premia Over Time

The core results in this paper are based on cross sectional analysis, and while we have addressed concerns regarding identification to the extent possible, we cannot entirely rule out that the results are driven by other omitted variables or endogenous plant location. Therefore it is valuable to examine whether our relationships survive when variation is within firm. A subset of firms in a subset of countries (twelve of our sample of 19) were re-interviewed during the sample period (2005-2010).

We begin by examining whether our firm level relationship between degree share and

[28] This is a form of the over-identification test, and a similar strategy is used by Card (1995) when estimating the returns to schooling. He allows distance to have a direct effect, and uses distance interacted with family variables as the excluded instrument for college education

[29] In general, we might expect there to be upward bias, but a negative bias could occur if for example, communication technologies that are complementary with management practices, and raise management scores when employed, also reduced the requirement for skilled workers. It could also reflect attenuation due to measurement error in firm human capital (which is a survey response).

[30] The average firm in the sample has a degree share of 14 per cent. In this indicative experiment, we double the degree share to 28 per cent. This implies an increase in the natural log of the degree share of around 0.7. Multiplying this by the coefficient on degree share gives a 0.3 standard deviation rise in management scores (0.7*0.42). The average plant in the sample has 164 employees. This experiment would involve raising the employees with a degree from 23 to 46.

management practices survives when we include firm fixed effects (Table 3.5.6). Column (1) is a simplified version of the endogenous OLS regressions in Table 3.5.5, column (1), estimated on the panel sample for comparison. This sample includes all firms that were interviewed in more than one wave over the period 2005-2010. Management scores and control variables were interpolated between survey waves so that observations are annual. Column (2) includes firm level fixed effects. The coefficient falls by nearly two thirds, but is still highly significant. This suggests that firms increasing their share of skilled workers over time are also improving their management practices. The smaller magnitude of the coefficient in the fixed effects specification may indicate that the omitted variables were positively correlated with both skills and management practices (in contrast to the IV findings), but it could also reflect attenuation due to measurement error in firm degree share which becomes more of an issue in the panel.

Moving now to the regional skill premium analysis, we also find some (more tentative) evidence that our effects are not driven entirely by unobserved factors. Column (3) shows the cross sectional relationship between the management z-score and the log of the wage ratio[31], for the ten countries in the panel where annual wage ratio data were available.[32] We drop capital regions, which we have seen before tend to dampen our results using skill premia.[33] This shows a significant negative relationship between management and the skill premium, as before. Column (5) adds firm fixed effects and our coefficient is now smaller, and significant at the 10 per cent level. This specification is demanding on the data as it requires variation within the firm in response to changes in regional skill prices over a short time frame.

Taken together, we consider that these results offer further support for the skill biased management hypothesis, indicating that our cross sectional results are not merely driven by firm level unobservables.

[31] We use this measure rather than the degree dummy coefficient from regional regressions on micro labour force data used in the cross section as there were insufficient observations in some region-year cells to calculate the latter measure robustly on an annual basis.

[32] These are Australia, France, Germany, Greece, Italy, Japan, Poland, Sweden, UK and US. Japan and Poland were not included in our core cross section analysis, as we were not able to obtain the microdata to run wage regressions. However, ready-made regional average wages (for skilled and unskilled workers respectively) were purchased from the statistical agencies in these countries. We note that the results in this table are very similar when Japan and Poland are excluded. In addition, to be consistent with our cross section analysis, we exclude India from these regressions, but the coefficient is only slightly smaller when India is included.

[33] The coefficient is negative, but smaller in magnitude when capital regions are included.

Table 3.5.6: Panel Regressions

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)
Ln(1+degree share)	0.223***	0.0854***		
	(0.0256)	(0.0251)		
Ln(wage ratio)			-0.802**	-0.323*
			(0.318)	(0.187)
Observations	7,048	7,048	5,358	5,358
Number of clusters	218	218	164	164
General controls	yes	yes	yes	yes
Industry dummies	yes	no	yes	no
Region dummies	yes	no	no	no
Firm fixed effects	no	yes	no	yes

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Sample includes all firms that were interviewed in more than one wave over the period 2005-2010. Management scores, degree share and general controls were interpolated between survey observations. All columns include country-year dummies. General controls include firm and plant employment and MNE status in column (1) and (3) (this drops out when firm fixed effects are included).

3.5.5.2 Performance Equations

Using the subsample of firms where sales data are available, we estimate basic production functions to examine interactions between management scores and distance to university. The results are in Table 3.5.7.

Column (1) is a simple regression of the natural log of sales on labour, capital, firm and industry controls[34] plus region fixed effects, but excluding firm level human capital. Column (2) includes distance to university showing that is negatively, but insignificantly associated with productivity. The interaction between management practices and distance is negative, but also not significant at conventional levels. Column (3) constrains the sample to single-plant firms, and the interaction term becomes much larger in magnitude and significant at the five per cent level, suggesting that single-plant firms benefit less in terms from raising management scores when far from universities. Column (4) shows that this result is not there for multi-plant firms. In further results (not reported here) we check that similar interaction effects do not exist for labour and capital. We take this analysis as

[34] We include 2 digit sic dummies and full noise controls (including a full set of analyst dummies), hours worked, plant age and dummies for missing values. We mean-code missing values of capital and employees, and include a dummy to indicate this. Capital is missing for 24% of the sample, and employment is missing for 3% of the sample). Results are robust to dropping these observations. Materials are not included here, as this variable is missing for 75% of the sample.

Table 3.5.7: Performance Equation Regressions

Dependent variable: Ln(Sales)	(1)	(2)	(3)	(4)
Management Z-score	0.104***	0.116***	0.189***	0.0596
	(0.0243)	(0.0283)	(0.0665)	(0.0370)
Ln(capital)	0.521***	0.520***	0.407***	0.551***
	(0.0568)	(0.0567)	(0.0607)	(0.0644)
Ln(labour)	0.493***	0.493***	0.483***	0.477***
	(0.0546)	(0.0546)	(0.0791)	(0.0636)
Distance		-0.0508	-0.0692	-0.0976*
		(0.0377)	(0.0647)	(0.0542)
Management Z-score x Distance		-0.0298	-0.170**	0.0405
		(0.0357)	(0.0716)	(0.0506)
Observations	4,833	4,833	1,306	3,527
Number of clusters	276	276	219	268

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. The sample of 4,833 plants are the subsample of the 6,363 plants in our distance analysis for which sales data are non missing. Where missing, capital and labour are mean-coded and a dummy variable included to indicate this. All columns include region and year fixed effects, 2 digit sic dummies and noise controls. Log hours and log plant age are controlled for (mean-coded if missing, with dummies to indicate this). Column (3) is estimated on the sample of single-plant firms. Column (4) is estimated on multi-plant firms.

further evidence of complementarities between skills and management practices, though this appears to be the case only for single-plant firms.

3.6 Conclusions

We have presented robust evidence that skills and management practices are complements using a newly analysed dataset on international universities and newly collated data on international subnational skill prices. Our proxy for skills access at the firm level is a measure of distance to closest university. Firms closer to universities have both higher degree share and management scores. These results can help us to understand one of the channels through which universities affect regional economic performance (Valero and Van Reenen, 2018). Using our estimates of regional skill premia, we provide evidence that universities might shift the supply and relative price of skills, which we then show are related to firm human capital and management scores.

We revisit the endogenous relationship between firm skills and management practices and use distance as an instrument for firm skills to gain a better understanding on the likely sign of the bias. The results are indicative due to the caveats discussed, but imply that the basic OLS relationship is biased downwards. In our preferred specification, doubling the firm level degree share implies a 0.3 standard deviation increase in management scores, which accounts for over half the difference between the management practices of the average US and UK firm. Drawing on the analysis by Bloom, Sadun and Van Reenen (2017), we can calculate what this means for productivity: an increase in management scores of 0.3 standard deviations could lead to around 3 per cent higher productivity.[35] Of course an increase in skilled workers can also be expected to raise productivity via a general human capital effect which is not captured here.

Complementarity between productivity enhancing management practices and general human capital is relevant for policymakers seeking ways to improve management in lagging firms, and productivity in general for two main reasons. First, complementarity implies that policies to raise human capital do not only raise productivity via a direct impact on worker skills, but also via an indirect effect as firms with a skilled workforce are more likely to adopt better management practices. Second, it implies that the payoffs from implementing polices to raise general human capital and policies specifically aimed at improving management practices (such as managerial training) are higher when such polices are implemented together. Similarly, the evidence presented in this paper suggests that managers seeking to implement or maximise the effectiveness of modern management practices should ensure that they recruit sufficiently skilled workers and managers.

There are a number of directions for future work. First, the measure of firm level human capital used in this paper (degree share) does not account for skills acquired from vocational education or on-the-job training. Future work will seek to understand better the specific types of skill that are relevant with respect to modern management practices, and how these can best be acquired. Second, the analysis in this paper is based on the manufacturing sector and it would be valuable to explore whether there is evidence of similar complementarities in the service sectors which dominate as a share of GDP in advanced economies like the US and UK.[36] Finally, it would be interesting to consider how workforce skills might complement different manager types (Bandiera et al., 2017), and how these interact with management practices as determinants of firm performance.

[35] As discussed in in Bloom, Sadun and Van Reenen (2017), causal estimates of the impact of management practices on total factor productivity have showed that increasing WMS style management scores by one standard deviation increased TFP by 10 per cent (Bloom et al., 2013). Therefore, the impact of raising management scores by 0.3 standard deviations would be 3 per cent higher TFP. Associations estimated on the international data in Bloom, Sadun and Van Reenen (2017) are of similar order of magnitude.

[36] The WMS has been conducted in other sectors, and national statistics offices are beginning to conduct their own management surveys across sectors, for example the Management Practices and Expectations Survey carried out by the UK's Office for National Statistics in 2018.

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3.A Data Appendix

3.A.1 World Management Survey

We use WMS survey waves conducted between 2004 and 2010, across 19 countries. These countries are: Argentina, Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Italy, Japan, Mexico, New Zealand, Poland, Portugal, Sweden, United Kingdom and United States. Ireland was also surveyed, but it is excluded from our analysis because it does not use post codes and hence it was not possible to accurately identify the location of the firms.

Here we describe the key features of the data and how it is used in this paper. Further details on the survey methodology is found in Bloom and Van Reenen (2007) (see also Bloom, Sadun and Van Reenen (2017) for more recent updates) and at the WMS website (http://worldmanagementsurvey.org/).

The WMS Sample

The sampling frame in the WMS was based on firm-level accounting databases, which provide sufficient information on companies to conduct stratified telephone surveys (company name, address and a size indicator). The sampling frame was all firms with a manufacturing primary industry code with between 50 and 5000 employees on average over the most recent three years of data prior to the survey.[37]

Scoring Management

The survey evaluation tool defines 18 management practices in four broad areas. Each is scored from 1 (worst) to 5 (best practices). Table 3.D.7 lists the 18 dimensions and the nature of questions asked. These areas were developed together with an international consulting firm as processes that, if adopted, should be expected to raise performance. Innovative steps were taken to maximise the quality of data: in particular the use of a "double-blind" interview method to reduce biases; open ended questions, and careful selection of interviewers and interviewees. Internal validity is tested by re-interviewing (with a different interviewer and interviewee) a sub-sample of firms. There was a positive and highly significant correlation between the scores from first and second interviews. The validity of the interpretation of high management scores as "good" management practices is supported by the existence of strong positive associations between management scores the scores with observable measures of firm performance: including sales, profitability

[37] In Japan and China, this was 150-5000 since the database used, BVD Oriana, only samples firms with more than 150 employees.

and survival probability, within and across countries. We normalise the management score to a mean zero, standard deviation one Z-score - across all countries and firms in the sample.

Other Variables from WMS

In order to geocode the plants, we required post codes. Detailed plant location data (other than region) were not collected in the original surveys. A separate project was conducted during 2011 to collect post-codes of the plants in the survey. This project was able to yield a 97.5 per cent response from the sampled firms.

Information on plant-level skills was collected in the surveys. Interviewees were asked what share of the total workforce, managers and non managers had degrees.

Consistent with Bloom and Van Reenen (2007) and subsequent papers, we used a number of other variables as controls, and for heterogeneity analysis. These include: number of employees in the plant and firm, plant age, MNE status, listed status, whether the plant belongs to a multi-plant firm, union representation and 2 digit SIC industry codes. We also add survey controls in our regressions to reduce noise. These include the gender, tenure and seniority of the manager who responded, the day of the week and hour of the interview, the duration of the interview, a measure of interviewee reliability as coded by the interviewer, and dummy variables to indicate the interviewer.

Missing values for plant employment, firm employment and interview noise controls were imputed using the average of these variables and a dummy variable is included in regressions where this is the case. For plant age, we followed the following imputation strategy. We first use firm age if that was available. Otherwise, we "hot-decked" plant age using regressions of plant founding dates on all other regressors for the sample that was not missing plant age.[38] We experimented with a simpler strategy of using the region average plant age and found similar results.

Financial data used in the performance regressions were sourced from accounting databases, as described, for example, in Bloom and Van Reenen (2007).

3.A.2 World Higher Education Database

The World Higher Education Database (WHED) is a database of higher education institutions around the world compiled by the International Association of Universities, in collaboration with UNESCO.[39] The WHED can be accessed online for a fee, and we

[38] The full list of covariates is the same as that used in our core regressions.
[39] For more information see: http://www.whed.net/home.php

obtained underlying data as at 2010. The key information relevant for this study includes: details on location, founding date and academic divisions (for example business, social sciences, law, medicine, science, arts and humanities). A full description of this database is available in Valero and Van Reenen (2018).

3.A.3 Geographic Data

Our empirical strategy requires measurement of the distance between plants and universities. Based on their postcodes, we geocoded plants and universities using the GeoPostcodes database. Drive times and distances between plants and universities were then calculated using google maps. Additional geographic information was then added using GIS software.

GeoPostcodes Database

The GeoPostcodes database is a commercial website providing data on the region, city, longitude and latitude of postal codes in countries.[40] We purchased country-level databases for 18 of our countries in March 2012.[41] We use this database to match postal codes to geographic coordinates and regions. In Table 3.D.8 we show the geocoding success rates across countries for WMS plants and WHED universities. On average, there are high levels of success- with a 96 per cent match for plants and 95 per cent match for universities.

A fraction of plants and universities appear to be in the same postcode and thus have the same geographic coordinates (this affects 10 per cent of the plants). This could be due to postcodes being fairly large geographies in certain cases or measurement errors in the postcodes. In robustness checks we exclude these plants and find similar results.

Google Drive Times

We calculate the drive times between each plant and its nearest university. This was done using the `traveltime` command in stata.[42] This command uses the geographic coordinates of two points and uses google maps to calculate the drive time (in hours) between them. A corresponding driving distance (in km) is also calculated. To minimise computing times we limited the search of the nearest university within a 100km Euclidean radius of each plant. Where a plant did not have a university within this radius, we find

[40] For more information, see: http://www.geopostcodes.com/UK

[41] In the UK we used the `geocode` command in stata to geocode the plants and universities. Information on this command is available at https://ideas.repec.org/c/boc/bocode/s457450.html, it uses googlemaps to geocode postal codes

[42] Information on `traveltime` can be found here: http://ideas.repec.org/c/boc/bocode/s457449.html

the nearest university at any distance and winsorised the resulting drive times using the regional maximum. This was done to minimise outlier bias.[43]

Drive times in google maps are calculated using information from GPS-enabled devices of users. To ensure that seasonality or varying traffic conditions were not affecting our results, we calculated another set of drive times several months later. The correlation between the two measures was 0.95.

CIESIN Population Data

We control for population density at the location of the plant. The Center for International Earth Science Information Network (CIESIN) provides the Gridded Population of the World (GPW) that depicts the distribution of population across the world in 2000.[44] We use GIS software to spatially intersect each plant with population density data from the CIESIN within a 100km buffer and find the average population density within that buffer.[45]

3.A.4 Regional Labour Force Data

Labour force data were obtained for 18 countries in the survey. The sources are outlined in Table 3.D.9. Microdata were obtained for 14 countries. In most cases these were labour force or household surveys, but in the case of Germany this was administrative labour force data. Where we were able to obtain access to microdata, we ran wage regressions by region. This allowed us to estimate the wage premium for having a degree, as the coefficient on a degree dummy, once other key characteristics were controlled for (experience, experience squared and gender). The specific years for which we were able to access data varied by source, but we tried to obtain as many years as possible between 2003 and 2010. For our cross-sectional analysis, observations were pooled over years in order to maximise the number of observations in a region, and therefore we included year dummies in the wage regressions. We also calculated raw wage ratios and the percentage of the labour force with a degree. These measures of the relative price of skills, or quantity of skills are used in the robustness. We calculated yearly raw wage ratios for use with the

[43] This affected 1.4 per cent of the sample. In robustness checks we exclude these isolated plants from the analysis and find no difference in results. It should be noted that for a fraction of the plants and universities that shared postcodes, the resulting google drive time would be reported as zero. In the robustness checks we excluded these plants and find no significant difference in results.

[44] Data are available here: http://sedac.ciesin.columbia.edu/data/collection/gpw-v3. Population density is represented as centroids in a features file. These centroids correspond to the smallest geography available for the country. For example in the US, this is the Census block group.

[45] We also checked the robustness of results with varying buffer sizes including using only the nearest centroid.

panel of WMS firms.

In the case of China, Japan, New Zealand and Poland, it was not possible to access microdata. However, regional aggregates of wage ratios and college share were available. For China, these came from summary statistics of the 2005 census; and for the other three countries the data were prepared for this purpose by the relevant statistical offices. It was not possible to obtain data for Portugal.

3.A.5 Final Analysis Sample Selection

An initial 10,163 interviews were available. Ireland was dropped because it does not use postal codes, and hence we could not establish the exact location of the plants. A further 416 interviews had missing or mis-reported postal codes. As mentioned previously, a few plants were interviewed multiple times either during follow up waves or during the same wave as a second interview for validity checks. In our core sample for cross sectional analysis, we keep the most recent interview of the plant, however, our results are robust to keeping all interviews for each plant and running a pooled cross section. We drop 785 observations with missing observations of firm level degree share which is the key (endogenous) explanatory variable; and 43 observations that are singletons in a particular region. This results in a final analysis sample of 6,363 plants for our analysis using distance to universities.

For consistency, the sample we use for the regional analysis is a subsample of this, consisting of 4,553 plants in the 13 countries for which we were able to calculate what we consider to be reliable regional skill premia from regional wage regressions. The final sample for the regional analysis drops an additional six observations in two regions (Arica y Parinacota and Los Rios in Chile which both became operational in 2007) where population data were not available in our regional dataset (we use regional population data from Gennaioli et al. (2013) to calculate weights for the regional regressions). We exclude India, where the sample sizes in the source data (NSS) by region were often small and likely to give unreliable estimates - in particular in some states there were very few observations in the manufacturing sector, or with degree level education. We include India in the robustness (see Table 3.D.11, row (17) and our coefficient on the skill premium is dampened slightly but remains highly significant). Results are robust to alternative sample specification, including keeping observations where firm level degree share is missing, keeping all survey waves or using the raw wage ratio which was available for more countries as a ready-made regional aggregate.

3.B Robustness Tests on Core Results

We report the main experiments on our core distance specification Table 3.D.10. The sample of 6,363 plants is used unless otherwise stated. In Panel A we check the standard errors, clustering at the country level, university level (Cameron et al, 2011) and allowing a spatial aspect using Conley standard errors. None of these adjustments affect the significance of the result.

We might worry that the distribution of drive times is skewed to the right, as shown in Figure 3.4.1 and that a simple linear relationship between drive times and management practices is not the best representation of the data. In Panel B, we allow for non linearities in distance. First show that taking logs does not affect the sign or significance of the result. A quadratic in drive time a slightly larger coefficient, and higher order polynomials raise the standard errors, but the coefficient on drive time remains negative and of similar order of magnitude, We then include a number of additional geographic controls (Panel C). Adding a quartic in geography controls leads to a loss of significance though the magnitude of our coefficient remains similar, and including measures of population density has little impact. We experiment with different distance measures in Panel D: driving distance, straight line distance and the number of universities within a 100km radius. In each case, the coefficient on distance takes the expected sign, but significance is lost. More noise is to be expected as these measures do not take into account geographical or other relevant features.

Next we show that our result is not sensitive to sample selection. Keeping all survey waves increases noise, but the magnitude of the coefficient is unchanged. The same goes for dropping observations so that the sample is consistent with that used for the regional analysis, and excluding firms with the same postal code as their closest university. Dropping winsorised observations strengthens the result, and dropping capital regions has no effect.

Panel F uses more granular fixed effects. First, we include country-year fixed effects and this does not change our result. We then turn to more demanding specifications, comparing observations in increasingly smaller cells - first region-sector, then county and finally city - dropping cells with only one observation. Significance is lost but the sign of the relationship is still negative. Finally, we show that using 3 digit industry dummies instead of 2 digit has no effect on the magnitude or significance of our main result.

Analogue robustness checks on the skill premium regressions are in Table 3.D.11. In general, the sign of the relationship is robust to different assumptions, but the significance of the relationship is lost in some cases. In particular, when standard errors are clustered at the country level (Panel A), or when regressions are unweighted (Panel B). More noise is to be expected in the data unweighted by some measure of population, as skill premia are likely to be worse measured in less populous regions within a country. In Panel C, additional controls are included and in general, the results remain significant. In particular, the inclusion of local population density does not affect the size or significance of the coefficient on degree premium.

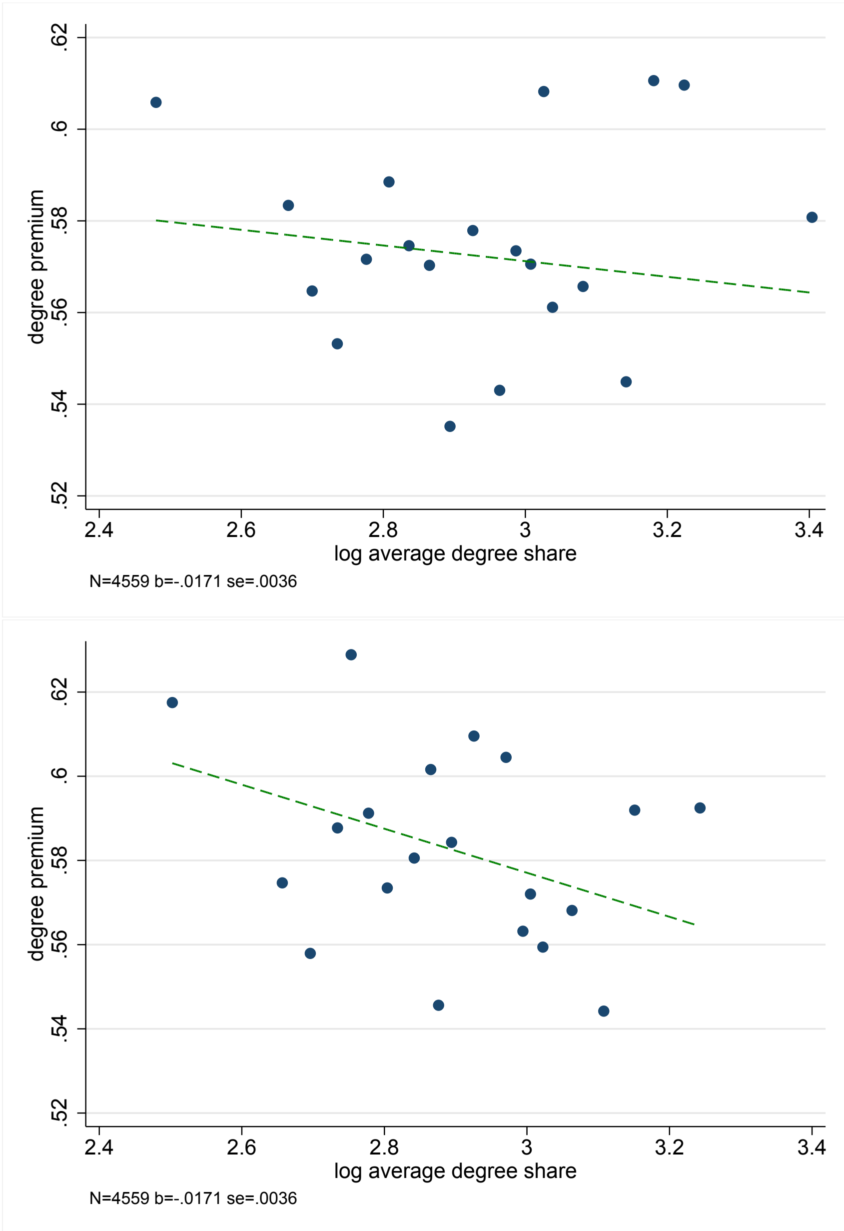
We also explore whether the expected relationships exist for alternative measures of regional skills, such as raw regional wage ratios or various quantity measures such as regional degree share or years of education. In general, the signs are as expected, but results not significant in these other measures. The regional measure of university presence, universities per million people, does have a positive and significant relationship with management practices.

Finally, in Panel E we show that the result is robust to alternative sample choices: keeping all survey waves, keeping India, firms with missing degree share or dropping capital regions (which actually strengthens the result in magnitude and significance).

Robustness tests on the IV regressions are summarised in Table 3.D.12, These follow a similar structure to the robustness on the core distance specifications, and overall, the coefficient of firm degree share remains positive, of similar magnitude and significance across robustness tests.

3.C Appendix Figures

Figure 3.C.1: Regional skill Premium and Degree Share



NOTES: Scatter plot of average regional skill premium on average regional degree share within 20 evenly sized bins. Variation is within country. The solid line represents the line of best fit.

3.D Appendix Tables

Table 3.D.1: Summary of Data at the Country Level

		Management Z-score		Degree Share (%)		Distance (hours)		Skill Premium	
	# plants	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Argentina	232	-0.27	1.06	10.09	12.11	0.52	0.90	0.68	0.07
Australia	400	0.07	0.86	11.97	14.12	0.53	0.60	0.29	0.03
Brazil	519	-0.34	1.01	11.00	12.60	0.22	0.34	0.95	0.06
Canada	371	0.35	0.93	11.58	13.77	0.63	0.83	0.40	0.05
Chile	264	-0.28	0.93	14.17	13.56	0.78	0.72	0.83	0.09
China	509	-0.32	0.70	10.35	13.06	0.74	0.76	-	-
France	255	0.11	0.80	13.57	15.58	0.63	0.46	0.39	0.03
Germany	292	0.47	0.84	13.91	14.74	0.36	0.22	0.60	0.03
Greece	174	-0.41	1.24	17.36	16.10	0.46	0.47	0.32	0.02
India	648	-0.56	1.04	20.65	21.61	0.35	0.47	-	-
Italy	170	0.15	0.91	14.86	14.59	0.59	0.32	0.45	0.07
Japan	97	0.46	0.85	31.78	21.38	0.11	0.25	-	-
Mexico	179	-0.00	1.06	22.48	21.49	0.16	0.15	0.96	0.09
New Zealand	143	-0.14	0.83	11.37	14.44	0.40	0.43	-	-
Poland	233	-0.04	0.95	20.20	17.83	0.32	0.31	-	-
Portugal	174	-0.25	0.91	9.36	9.88	0.30	0.19	-	-
Sweden	246	0.45	0.79	15.37	17.34	0.61	0.48	0.34	0.03
United Kingdom	784	0.10	0.97	12.29	15.75	0.42	0.42	0.54	0.03
United States	673	0.59	0.92	19.12	18.81	0.31	0.28	0.58	0.06

NOTES: N=6,363. *Management Z-score* is the standardised simple average of all 18 management questions from the World Management Survey. Degree share is the plant-level percentage of total workforce, with a degree. *Distance* is the drive time in hours from the plant to the nearest university. *Skill premium* is the coefficient on a degree dummy from regional wage regressions.

Table 3.D.2: Additional Descriptive Statistics

	Mean	S.D	Min	Max	Count
University characteristics					
Uni has business finance	0.62	0.48	0	1	6363
Uni has law or social sciences	0.74	0.44	0	1	6363
Uni has medicine or science	0.76	0.43	0	1	6363
Uni has arts humanities	0.71	0.45	0	1	6363
Uni has all listed depts	0.15	0.36	0	1	6363
University founding	1941.8	98.5	1088	2011	6363
Missing founding	0.054	0.23	0	1	6363
University founded before plant	0.60	0.49	0	1	6363
Google maps and GIS variables					
Driving distance	0.27	0.52	0	13.5	6363
Straightline distance	0.22	0.57	0	35.7	6363
No. of universities within 100km	34.3	55.3	0	441	6363
No. of universities within 50km	19.4	38.1	0	316	6363
Avg pop density within 50km radius	1.69	2.51	0	20.9	6363
Avg pop density nearest centroid	3.00	7.29	0	84.9	6363
Plant and university share postal code	0.11	0.31	0	1	6363
Distances are winsorised	0.016	0.13	0	1	6363
Regional skills variables					
Ln(average regional wage ratio)	0.65	0.33	0.17	2.02	5541
Mincer years of education coefficient	0.10	0.039	0.033	0.21	4559
Average years of education	9.20	2.83	3.02	12.8	6326
Average regional degree share	0.20	0.13	0.016	0.50	6352
For Performance Regressions					
Ln(Sales)	10.5	1.74	0	16.6	4833
Ln(Capital)	9.48	1.79	-1.85	16.0	4833
Missing Capital	0.24	0.43	0	1	4833
Ln(Employees)	5.74	1.08	0	12.5	4833
Missing Employees	0.035	0.18	0	1	4833
Ln(Hours)	3.76	0.12	3.56	4.38	4833
Missing Hours	0.0081	0.089	0	1	4833

NOTES: The subject variables are dummies indicate provision at nearest university. *University founding* gives founding year. *Driving distance* is the google driving distance ('00km) to nearest university. *Straightline distance* is the straight line distance ('00km) to nearest university. *No. universities within 100km (50km)* is a count within the given radius. *Avg pop density within 50km radius* and nearest centroid are calculated using GIS software. An indicator is created for plants and universities that share a postcode, and for plants with no university within 100km radius (distance is winsorised to regional maximum). *ln(average regional wage ratio)* is based on calculation from microdata or ready-made data as shown in Table 3.D.9.*Mincer years of education coefficient* is recovered from regional wage regressions. *Average years of education* and *average college share* are measures of skills quantities, obtained from Gennaioli et al. (2013). The productivity sample is conditioned on plants with non-missing sales. Missing values of capital or employees are mean coded. Financial data are sourced from accounting databases. Hours worked is a survey question.

Table 3.D.3: Within Region Variation

	Regions	Difference 90th−10th Percentile Plant, Median region		
		Management Z-score	Degree share (%)	Distance (hours)
Argentina	15	2.20	1.70	0.42
Australia	6	2.13	2.74	1.77
Brazil	19	2.50	2.56	0.72
Canada	9	2.39	2.40	1.30
Chile	14	1.85	1.56	0.61
China	26	1.66	2.56	1.40
France	20	2.06	2.25	0.83
Germany	15	2.05	2.27	0.50
Greece	9	2.88	2.55	0.70
India	22	2.52	2.08	0.68
Italy	13	2.46	2.09	0.70
Japan	19	1.61	1.55	0.00
Mexico	19	2.31	2.02	0.19
New Zealand	10	1.77	2.55	0.84
Poland	16	2.44	2.16	0.74
Portugal	11	2.29	2.31	0.48
Sweden	19	1.90	2.50	0.87
United Kingdom	12	2.54	3.07	0.56
United States	40	2.18	2.58	0.55

NOTES: Number of regions=314. This table shows region-level variation in Management Z-score, Degree Share and Distance variables, by country.

Table 3.D.4: Heterogeneity by University Characteristics

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)	(5)	(6)
Subject is:	Bus	Law, soc. sci	Med, Sci	Arts, Hum.	All listed	
Distance	-0.052*	0.002	-0.008	-0.033	-0.041*	-0.074***
	(0.029)	(0.051)	(0.051)	(0.046)	(0.021)	(0.027)
Distance x "subject"	0.003	-0.060	-0.049	-0.019	-0.051	
	(0.032)	(0.051)	(0.053)	(0.047)	(0.046)	
"subject"	0.003	0.045	0.024	-0.000	0.025	
	(0.029)	(0.029)	(0.034)	(0.035)	(0.035)	
Distance x before						0.042
						(0.039)
Before						-0.003
						(0.028)
Observations	6,363	6,363	6,363	6,363	6,363	6,363
Number of clusters	314	314	314	314	314	314

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Column (1) reproduces the core specification in Table 3.5.1, Panel A, column (4).

Table 3.D.5: Effects of Skills on Different Management Practice Groupings

Dependent Variable:	(1) Zman	(2) Zops	(3) Zmonitor	(4) Ztarget	(5) Zpeople
A: Distance					
Distance	-0.050***	-0.041*	-0.036	-0.065***	-0.031
	(0.019)	(0.023)	(0.023)	(0.022)	(0.022)
Observations	6,363	6,351	6,363	6,363	6,363
Number of clusters	314	314	314	314	314
B: Skill Premium					
Skill Premium	-0.737**	-0.443	-0.730**	-0.293	-0.934**
	(0.349)	(0.293)	(0.327)	(0.299)	(0.418)
Observations	4,553	4,550	4,553	4,553	4,553
Number of clusters	208	208	208	208	208

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Column (1) contains the specifications: Panel A, column (4) of Table 3.5.1, and Panel A, column (4) of Table 3.5.3. Columns (2) to (5) replicate this for different management practice groupings as the dependent variable.

Table 3.D.6: Extended IV Regressions

Dependent variable: Management Z-score Specification:	(1) OLS	(2) IV	(3) OLS	(4) IV
Ln(1+degree share)	0.155***	0.388*	0.156***	0.846**
	(0.014)	(0.225)	(0.014)	(0.399)
Distance X Business	-0.029	-0.006		
	(0.019)	(0.029)		
Uni has Business	0.011	-0.008		
	(0.025)	(0.032)		
Distance X Before			-0.004	0.088
			(0.026)	(0.074)
Uni founded before plant			0.019	-0.021
			(0.024)	(0.046)
Distance				
Observations	6,363	6,363	6,363	6,363
Number of clusters	314	314	314	314
Instrument		Distance (Non-Business)		Distance (Founded After)
F statistic		11.08		7.094

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Standard errors are clustered at the region level in parentheses. Regressions contain full set of controls, consistent with column (5) in Table 3.5.1.

Table 3.D.7: WMS Management Practices

Categories	Score from 1 to 5 based on:
Operations	
1) Introduction of modern manufacturing techniques	What aspects of manufacturing have been formally introduced, including just-in-time delivery from suppliers, autonomation, flexible manpower, support systems, attitudes, and behavior?
2) Rationale for introduction of modern manufacturing techniques	Were modern manufacturing techniques adopted just because others were using them, or are they linked to meeting business objectives like reducing costs and improving quality?
Monitoring	
3) Process problem documentation	Are process improvements made only when problems arise, or are they actively sought out for continuous improvement as part of a normal business process?
4) Performance tracking	Is tracking ad hoc and incomplete, or is performance continually tracked and communicated to all staff?
5) Performance review	Is performance reviewed infrequently and only on a success/failure scale, or is performance reviewed continually with an expectation of continuous improvement?
6) Performance dialogue	In review/performance conversations, to what extent is the purpose, data, agenda, and follow-up steps (like coaching) clear to all parties?
7) Consequence management	To what extent does failure to achieve agreed objectives carry consequences, which can include retraining or reassignment to other jobs?
Targeting	
8) Target balance	Are the goals exclusively financial, or is there a balance of financial and non financial targets?
9) Target interconnection	Are goals based on accounting value, or are they based on shareholder value in a way that works through business units and ultimately is connected to individual performance expectations?
10) Target time horizon	Does top management focus mainly on the short term, or does it visualise short-term targets as a "staircase" toward the main focus on long-term goals?
11) Targets are stretching	Are goals too easy to achieve, especially for some "sacred" cows areas of the firm, or are goals demanding but attainable for all parts of the firm?
12) Performance clarity	Are performance measures ill-defined, poorly understood, and private, or are they well-defined, clearly communicated, and made public?
People Management	
13) Managing human capital	To what extent are senior managers evaluated and held accountable for attracting, retaining, and developing talent throughout the organisation?
14) Rewarding high performance	To what extent are people in the firm rewarded equally irrespective of performance level, or are rewards related to performance and effort?
15) Removing poor performers	Are poor performers rarely removed, or are they retrained and/or moved into different roles or out of the company as soon as the weakness is identified?
16) Promoting high performers	Are people promoted mainly on the basis of tenure, or does the firm actively identify, develop, and promote its top performers?
17) Attracting human capital	Do competitors offer stronger reasons for talented people to join their companies, or does a firm provide a wide range of reasons to encourage talented people to join?
18) Retaining human capital	Does the firm do relatively little to retain top talent or do whatever it takes to retain top talent when they look likely to leave?

NOTES: This table is taken from Bloom and Van Reenen (2010).

Table 3.D.8: Geocoding Success Rates for Plants in WMS and Universities in WHED

	WMS		WHED	
	No. plants	Geocode rate	No. universities	Geocode rate
Argentina	249	0.95	95	0.95
Australia	452	0.95	44	1
Brazil	591	0.94	1852	0.90
Canada	419	1	146	1
Chile	372	0.89	88	1
China	763	0.92	548	0.98
France	639	0.97	281	1.00
Germany	672	0.99	339	1
Greece	272	0.96	38	0.97
India	936	0.97	559	0.99
Italy	314	0.98	93	0.94
Japan	176	0.97	696	0.92
Mexico	190	0.99	1322	0.93
New Zealand	150	0.97	23	1
Poland	364	1	408	1.00
Portugal	311	1.00	114	0.86
Sweden	404	0.98	38	1
United Kingdom	1381	0.94	174	0.99
United States	1347	0.95	2184	1.00

NOTES: This table shows the geocoding success rates for WMS plants and WHED universities using the GeoPostcodes database. The 9081 universities represent the population of universities in the WHED database for the relevant countries

Table 3.D.9: Labour Force Survey Data Sources

Country	Source	Years used
Microdata:		
Argentina	Permanent Household Survey (EPH), Insituto Nacional de Estadística y Censos (INDEC)	2008-10
Australia	HILDA Survey, Melbourne Institute	2005-10
Brazil	National Household Sample Survey (PNAD), Instituto Brasileiro de Geografia e Estatística (IBGE)	2003-2009
Canada	Labour Force Survey, Statistics Canada	2003-2010
Chile	National Socioeconomic Characterization Survey (CASEN), Ministry of Social development	2006, 09
France	Enquete Emploi, Institute National de la Statistique et des Etudes Economiques (INSEE), Centre Maurice Halbwachs	2003-2010
Germany	Sample of Integrated Labour Market Biographies (SIAB), Research Data Centre (FDZ) of the Germany Federal Employment Agency (BA) at the Institute for Employment Research (IAB)	2003-10
Greece	Labour Force Survey, Hellenic Statistical Authority (ELSTAT)	2003-10
India	National Sample Survey, Employment and Unemployment	2004, 06, 08
Italy	Historical Database of the Survey of Italian Household Budgets	2004, 06, 08, 10
Mexico	National Income and Expenditure Survey (ENIGH), Instituto Nacional de Estadística y Geografía (INEGI)	2006, 08, 10
Sweden	Regional Aggregates obtained from analysis at Jonkoping University, using Statistics Sweden microdata (MONA)	2005, 07, 08, 10
UK	UK Labour Force Survey, UK Data Service	2003-10
US	IPUMS-CPS	2003-10
Regional data:		
China	China 2005 Census	2005
Japan	National Statistics Centre, Ministry of Internal Affairs and Communications	2006-10
New Zealand	Statistics New Zealand	2003-10
Poland	Central Statistical Office, Poland	2004, 06, 08, 10

NOTES: Citation requirements for Canada, France and Germany follow. *Canada:* The analysis on Canada is based on Statistics Canada Microdata file: Labour Force Survey, which contains anonymized data collected from 1987 to 2010. All computations on these microdata were prepared by the authors, and the responsibility for the use and interpretation of these data is entirely with the authors. *France:* Sources cited as Emploi (en continu) - série 2003 - 2012 (version production et recherche) - [fichier électronique], INSEE [producteur], Centre Maurice Halbwachs (CMH) [diffuseur], and Emploi (en continu) - série 2003-2012 - () [fichier électronique], INSEE [producteur], Centre Maurice Halbwachs (CMH) [diffuseur] *Germany:* This study uses the factually anonymous Sample of Integrated Labour Market Biographies (version 1975-2010). Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

Table 3.D.10: Robustness on Distance Regressions

	Specification	Coefficient on Distance	(S.E.)
(1)	Core specification	-0.050***	(0.019)
	A. Standard errors		
(2)	Cluster at country	-0.050**	(0.021)
(3)	Cluster at university	-0.050***	(0.019)
(4)	Conley standard errors, 100km	-0.050***	(0.018)
	B. Non Linearities in distance		
(5)	Ln(1+drive time)	-0.105***	(0.039)
(6)	Quadratic in drive time	-0.081**	(0.035)
(7)	Cubic in drive time	-0.099*	(0.055)
(8)	Quartic in drive time	-0.122*	(0.073)
	C. Additional geographic controls		
(9)	Quartic in geography controls	-0.037*	(0.020)
(10)	Average population density within 50km	-0.051***	(0.018)
(11)	Average population density nearest centroid	-0.057***	(0.018)
	D. Alternative measures of distance		
(12)	Driving distance ('00km)	-0.050*	(0.028)
(13)	Straight line distance ('00km)	-0.026	(0.020)
(14)	No. universities within 100km	0.001	(0.000)
	E. Sample		
(15)	Keep all waves (N=8,074)	-0.041**	(0.018)
(16)	Skill premium sample (N=4,533)	-0.053**	(0.022)
(17)	Exclude same postal codes (N=5,669)	-0.042**	(0.019)
(18)	Exclude winsorised (6,261)	-0.066**	(0.025)
(19)	Drop capital regions (N=5,548)	-0.051**	(0.020)
	F. Fixed effects		
(21)	Country X year dummies	-0.050***	(0.019)
(22)	1,207 region X industry dummies (N=5,227)	-0.056*	(0.030)
(23)	724 county dummies (N=4,553)	-0.045	(0.031)
(24)	851 city dummies (N=2,756)	-0.209	(0.296)
(25)	152 3 digit SIC industry dummies	-0.049***	(0.296)

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Each row represents a different robustness check on Panel A, column (4) of Table 3.5.1.

Table 3.D.11: Robustness on Regional Skill Premium Regressions

	Specification	Coefficient on Skill Premium	(S.E.)
(1)	Core specification	-0.737**	(0.349)
	A. Standard errors		
(2)	Cluster at country	-0.737	(0.421)
	B. Weighting		
(3)	WMS weights	-0.879**	(0.404)
(4)	No weights	-0.312	(0.280)
	C. Additional Controls		
(5)	Quartic in geography controls	-0.196	(0.332)
(6)	Average population density within 50km	-0.721**	(0.351)
(7)	Average population nearest centroid	-0.740**	(0.341)
(8)	Regional geographic variables	-0.659*	(0.376)
(9)	Analyst dummies	-0.329	(0.332)
(10)	Country X year fixed effects	-0.700**	(0.348)
(11)	3 digit SIC industry dummies	-0.621*	(0.354)
	D. Alternative measures of regional skills		
(12)	Log average regional wage ratio (N=6,738)	-0.262	(0.171)
(13)	Mincer years of education coefficient	-1.145	(2.126)
(14)	Average years of education (N=7,814)	0.010	(0.034)
(15)	Ln(average regional degree share) (N=6,738)	-0.016	(0.062)
(16)	Ln(1+universities per million) (N=7,845)	0.074**	(0.033)
	E. Sample		
(17)	Keep all waves (N=5,649)	-0.817***	(0.312)
(18)	Keep India (N=5,199)	-0.583**	(0.254)
(19)	Keep firms with missing degree share (N=5,164)	-0.786**	(0.332)
(20)	Drop capital regions (N=3,880)	-0.925***	(0.258)

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. N=4,553 unless stated otherwise. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Each row represents a different robustness check on Panel A, column (4) of Table 3.5.3. Regional geographic variables include temperature, inverse distance to the coast, and cumulative oil production, and are sourced from Gennaioli et al (2013). WMS weights are calculated by dividing the number of plants in a region surveyed in the WMS by the number of plants in the country.

Table 3.D.12: **Robustness on IV Regressions**

	Specification	Coefficient on Degree share	(S.E.)
(1)	Core specification	0.420***	(0.142)
	A. Standard errors		
(2)	Cluster at country	0.420***	(0.143)
(3)	Cluster at university	0.420***	(0.153)
	B. Non Linearities in distance		
(4)	Ln(1+drive time)	0.393***	(0.132)
(5)	Quadratic in drive time	0.382***	(0.136)
(6)	Cubic in drive time	0.360***	(0.130)
(7)	Quartic in drive time	0.361***	(0.130)
	C. Additional geographic controls		
(9)	Quartic in geography controls	0.336**	(0.162)
(10)	Average population density within 50km	0.439***	(0.147)
(11)	Average population nearest centroid	0.468***	(0.140)
	D. Alternative measures of Distance		
(12)	Driving distance ('00km)	0.371**	(0.179)
(13)	Straight line distance ('00km)	0.388**	(0.183)
(14)	No. universities within 100km	0.413	(0.314)
	E. Sample		
(15)	Keep all waves (N=8,074)	0.329***	(0.127)
(16)	Skill premium sample (N=4,533)	0.498**	(0.196)
(17)	Exclude same postal codes (N=5,661)	0.372**	(0.156)
(18)	Exclude winsorised (6,260)	0.477***	(0.158)
(19)	Drop capital regions (N=5,548)	0.458***	(0.156)
	F. Fixed effects		
(20)	Country X year dummies	0.352***	(0.123)
(21)	1,207 region X industry dummies (N=5,227)	0.369**	(0.156)
(22)	724 county dummies (N=4,553)	0.265	(0.172)
(23)	2,756 city dummies (N=2,756)	0.166	(0.181)
(24)	152 3 digit SIC industry dummies	0.414***	(0.148)

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Standard errors are clustered at the region level in parentheses. N=6,363 unless stated otherwise. Each row represents a different robustness check on column (3) of Table 3.5.5.

Chapter 4

Industry in Britain: An Atlas[1]

[1] We would like to thank Steve Machin, Max Nathan and Nigel Rogers for their helpful comments. The Economic and Social Research Council have given financial support through the Centre for Economic Performance. The CEP and ESRC have no political affiliation or institutional view and all co-authors write in a personal capacity.

4.1 Introduction

Britain is a place where people worry about the geographic spread of industry. Take the following two quotes:

[1] *A policy of balanced distribution of industry and the industrial population throughout the different areas or regions in Great Britain; and of appropriate diversification of industries in those areas or regions would tend to make the best national use of the resources of the country.*

[2] *The maldistribution of the industrial population has been and is being still further intensified. Unemployment throughout the country is no real problem to-day. The most urgent problem is the attainment of full development, of the maximum use of our resources and the achievement of the fullest efficiency.*

Anyone that has followed the UK economy in recent years understands what these writers refer to. Employment is at record levels, but there are concerns about the productivity of British workers, wages, job security and the spread of economic activity and opportunity across the country.[2] In fact, both statements are over 60 years old. The first is from the 1940 "Barlow Report" which identified the unequal patterns of industry across the UK; the second is from a Parliamentary debate in 1957, which asked what had changed since 1940, concluding that little had.[3] Concerns that some regions of the UK are falling behind others, and that the location of companies helps explain this, are longstanding.

Agreement that something should be done about it is rarer. Determination to adopt policies that address regional disparities has ebbed and flowed over the past 50 years.[4] There are signs that the 2017 Parliament could see an intensification of efforts to seek a more even spread of industry in Britain. Chancellor Philip Hammond has said that a new "hands on" industrial strategy will help left-behind areas; shadow chancellor John MacDonnell has promised a "comprehensive" industrial strategy that would "spread wealth across the country", and a new industrial strategy with a regional focus is a large

[2] See Costa and Machin (2017) for a recent summary of the data on real wages and living standards at the national level in the UK.

[3] The Barlow Report (1940) was formally "The Report of the Royal Commission on Distribution of Industrial Population" one of its findings was that "The continued drift of the industrial population to London and the Home Counties constitutes a social, economic and strategical problem which demands immediate attention". The Commission suggested regional imbalance was of national concern, recommended the decentralisation of industry away from congested areas, and proposed a central authority to tackle the problem; a board for industrial location which would be responsible to the Board of Trade. See: http://discovery.nationalarchives.gov.uk/details/r/C8722

[4] Examples include the Distribution of Industry Acts of 1945 and 1950; geographic policies of the 1970s (known as Regional or Urban Policy) which attempted to shift industry away from cities seen as 'declining' including inner-city Glasgow (see Smith and Wannop, 1985), and, most recently the "Northern Powerhouse" agenda, a series of policies pursued by HM Treasury seeking to create an economic hub including Greater Manchester and the major cities of Yorkshire and Lancashire.

part of Liberal Democrat leader Vince Cable's economic strategy.[5] Reflecting this political interest Britain's main business department and finance ministry are working on a new "Industrial Strategy" which looks set for launch over the coming months.[6]

Summary of this paper

Despite the rising interest in addressing the UK's uneven economic performance, no one has published a comprehensive analysis setting out the latest facts on Britain's business geography. This paper begins to fill that gap. We use data on firms as the basis of a comprehensive mapping of UK Industry.[7] The full set of maps is presented as a separate document, including measures of industrial specialisation across sectors (at the SIC section level). This paper presents the most striking maps and findings together with some tentative conclusions.

Ten stylised facts stand out, many of which challenge the prevailing wisdom in the UK. We summarise these here, and expand in the next section.

1. **The three patterns of industry**. Using measures of industrial specialisation based on employment, we find that the location of business activity in Britain varies considerably by industry, and follows three broad patterns:

    - **Uniform**. Some industries are fairly evenly spread around the country, with a similar concentration of activity in most locations. Often, these industries provide products or services that must be sold locally: for example, retail services includes firms such as hairdressers and gyms. Outside large cities, agriculture is spread relatively evenly across the UK. More surprisingly, manufacturing is relatively evenly spread outside London.
    - **Scattered.** In these industries, activity is concentrated in a number of locations, creating a scatter of strong dots across the country. This includes firms operating in science and technology sectors and mining and quarrying. The fact that finance is scattered across multiple hubs is a challenge to the belief that banking only occurs in the South East.
    - **Single hub**. In these industries there is one location where activity seems to be concentrated. The creative sectors and information and communication

[5] See Phillip Hammond, interview on the local economy of Stoke on Trent (January 23rd 2017) and John MacDonnell speech (26th September 2016).

[6] See e.g. BEIS Building our Industrial Strategy, January 2017.

[7] See the Data Appendix for a description of key datasets, which are useful for analysing businesses in the UK.

technology are examples: in both activity is focused in London and the South East, though there are also pockets in cities such as Manchester and Edinburgh. Given the expectation that creative industries and "tech" are potential growth industries, this will concern those seeking a more even spread of opportunity in Britain.

2. **Firm size distribution**. Firm size matters for industrial performance: larger firms tend to invest more and have higher productivity. However, UK industry is dominated by small firms with around 99% of firms being classed as "small" (0-49 employees). So-called "non-employing" businesses (firms where the owner-manager is the only worker) are the largest category making up around three-quarters of firms in all regions. Our maps show that mid-sized firms (50-249) are relatively evenly spread across the UK; large firms are very sparsely spread: currently, only 55% of local authorities have 10 or more large firms. More encouragingly, maps showing the increase in mid-sized firms show that this growth is relatively evenly spread.

3. **Business demography.** The rate at which firms start up and go bankrupt is relatively evenly spread, with maps showing that these "births" and "deaths" are equally likely across UK regions. This suggests that the ease with which a company can be established and wound up are unlikely to be explain regional productivity differences.

4. **The spread of productivity**. The output per hour of a British worker varies considerably by location. At the bottom of the productivity scale is mid Wales; the countryside around Brecon is an area with little industry and agriculture as the main employer. At the other end of the scale there are three high-productivity hubs: the oil industry around Aberdeen, the area around Greater Manchester and a band of productivity in the South. Contrary to popular belief the high productivity of London does not spread into the South East but rather spreads west along the M4 towards commuter towns like Reading and Slough which have their own high productivity companies.

5. **Leader and laggard sectors.** The highest productivity sectors, real estate, mining and utilities, are small employers and so play little role in aggregate performance. Of the high employment sectors that drive national productivity the leading sectors are finance, information and communications, construction and manufacturing.

Professional, scientific and technical services vary within and across regions - this sector houses some very high productivity firms together with much weaker ones. However, it is important to consider high employment sectors with weak productivity, such as retail and wholesale trade, administrative services and accommodation and food services. Raising average productivity in these sectors could have a large aggregate effect due to their high employment shares.

6. **Innovation in the regions.** We use data on research and development (R&D) expenditure and patents to gauge innovation by region. In absolute terms, London and the South East dominate, accounting for nearly a third of business spending on R&D. However, in terms of R&D as a percentage of GDP, the East of England stands out. At a more disaggregated level, Britain's most innovative NUTS2 regions (equivalent to grouped counties, unitary authorities or districts) are East Anglia, Cheshire and Hertfordshire; reflecting the impact of Cambridge University, chemicals firms located along the River Mersey and pharmaceuticals and life sciences firms located in and around Hertfordshire.

7. **Unbalanced exporting.** Britain has a sizeable current account shortfall at 3.4% of GDP (Q1 2017). Only 11% of firms export and those that do export are most likely to be based in London, the South East or the East of England. The North East has the lowest share of exporters at fewer than 6% . A poor and unbalanced export performance has long been of concern, but Britain's exit from the EU will create new challenges in this area. It is estimated that all local authorities are likely to become worse off following Brexit, but that the largest impacts are expected to be in cities that specialise in finance and business services.[8] Understanding the local impacts of Brexit through changes to trade (together with immigration, FDI and innovation) will be crucial for policymakers developing an industrial strategy with region-specific elements.

8. **The UK's coastal malaise.** A number of maps outline concern about the economic performance of Britain's coastal towns. Maps of survival rates show that firms located near the coast are more likely to go out of business than those further inland. These areas also tend to specialise in accommodation and food services, which tend to be low productivity industries with a high churn of businesses. Other research

[8] See Dhingra and Overman (2017).

shows that skills are particularly weak in these areas, perhaps reflecting the demands of the local labour market.[9]

9. **The power of a single firm.** Some of the patterns in the regional data indicate local domination by single firms. For example, the high productivity in north Lancashire, Derby and Brentwood is influenced by the major plants of BAE Systems, Rolls Royce and Ford, respectively. Further examples are Tata Steel in Port Talbot and Airbus in Broughton (Flintshire), both in Wales. The same can also be true for service sector firms, for example Sky in parts of Scotland. The local impact of losing or gaining a large company can be large.

10. **The German benchmark**. It is well-known that the UK's aggregate productivity is far behind that of its key comparator countries: Germany, France and the US. We compare the economic performance of British regions to those in Germany. The resulting maps are concerning, showing that Britain's best performing regions (with the exception of Central London) are far behind the German average. Germany stands out as a multi-hub country, with around ten identifiable high-productivity areas: by contrast in the UK the South East dominates. Whilst Germany also faces regional challenges, with longstanding poor performance in East Germany, these poor performing regions are catching up. Whereas in Britain, the laggard regions appear to be falling further behind.

Next steps

The UK has good quality firm-level data, and it is crucial that this is put to best use in guiding policy. The LSE Growth Commission (LSE, 2017) made a series of recommendations to strengthen the institutions governing industrial strategy. A key component here would be the publication of an annual "Industrial Strategy Report" on the state of British business akin to the UK's other regular publications such as the *Inflation Report* and *Financial Stability Report* and the *Economic and Financial Outlook* which help guide and explain monetary and fiscal policy. This paper provides some of the types of analysis that could be usefully included and built upon in such a report. Further work is needed at more spatially and sectorally disaggregated levels, and there could be scope for more standardisation of ONS datasets, for example to provide detailed sectoral GVA for local areas on an annual basis allowing comparisons over time. Further improving the processes

[9] House of Commons Communities and Local Government Committee (2006), Coastal Towns Second Report of Session 2006-07.

for accessing and linking the micro-data would help researchers to conduct more detailed analyses.

This paper provides a snapshot of the current state of play, but it remains unclear what the optimal distribution of industry is, and therefore what the ultimate goal of regional policy should be. While this paper does not consider this question in detail, any industrial policy has to proceed cautiously and in full knowledge of facts on the ground. Broadly, the evidence suggests that area-based initiatives can lead to displacement rather than aggregate gains, though it is possible to design policies that deal with these issues.[10] Moreover, there are tensions between "jam-spreading" (spreading resources across locations) and the ability to build up successful hubs that exploit network effects.[11] It is increasingly recognised that greater local control is important: more space for local authorities to experiment with different types of policy. This, together with improved data collection and evaluation should help increase policy effectiveness.[12]

Policies targeted at particular regions and/or sectors are likely to involve trade-offs and claims from competing stakeholders. The UK needs a new institutional framework to help make these tough decisions. The guiding principle should be the elimination of market failures, and the new framework should inject some form of independent oversight, perhaps borrowing from the structures and processes used by the Bank of England, the Office for Budget Responsibility and the UK's highly-regarded independent competition authorities.

4.2 Ten Stylised Facts on UK Business

4.2.1 Fact 1: Three Patterns of Industry

There are a number of reasons that the location and type of business activity matter. In all countries productivity varies considerably by industry - manufacturing is more productive than retail services in every OECD country for example - so it may be the case that regional productivity differences are driven by industrial patterns. Moreover, where an industry exhibits significant "network externalities" (that is, if it pays to be in an area where competitor firms are located) then the presence of an agglomeration or a "cluster" of companies has been shown to be an important driver of firm and regional economic

[10] See for example Einio and Overman (2016) and Criscuolo et al. (2016).
[11] See Overman (2013).
[12] See Nathan and Overman (2013) for discussion of the appropriate spatial scale for industrial policy interventions, including the delivery of horizontal policies in specific places, or in a decentralised fashion.

performance. The challenge for policymakers however is that explicit cluster policies have generally been found to be ineffective, and a key question is to consider the appropriate spatial scale for more horizontal interventions to address market failures (for example in the supply of skills or access to finance) which might stimulate or enable agglomerations to grow.[13]

There are a number of ways that business activity can be measured in spatial terms:

- **Firm numbers**. A basic measure of business activity is a simple count of businesses in a given area. For detailed spatial analysis, it is usually more appropriate to use the "local unit" or "plant" which reflects the location of activity, rather than the business enterprise - for which the location reflects the company's headquarters (many companies have numerous plants). It might be that certain areas have more firms or employment due to their higher population, therefore it is often more relevant to consider the number of firms normalised by population, a measure of business "density". We consider those of working age.

- **Employment data**. Businesses vary in size, so looking at employment can give a better measure of the extent of economy activity. Again, it is useful to consider employment as a percentage of the local population. Another interesting measure for understanding the nature of local economic activity is the share of a particular sector's employment in total local employment.

- **Industrial specialisation.** The location quotient (LQ) gives a measure of industrial specialisation in a particular region. The LQ compares a sector's local share of employment with that sector's share in national employment. A location quotient greater than one for a particular area suggests that the area is specialised for a particular industry. This measure can also be calculated based on number of firms.[14]

- **Geographical concentration of industries.** There are a number of measures that can be used to understand whether specific industries are geographically concentrated in a small number of areas, or more evenly spread around the UK. One simple index is the Herfindahl-Hirschman index (HHI) for geographical concentration. For each

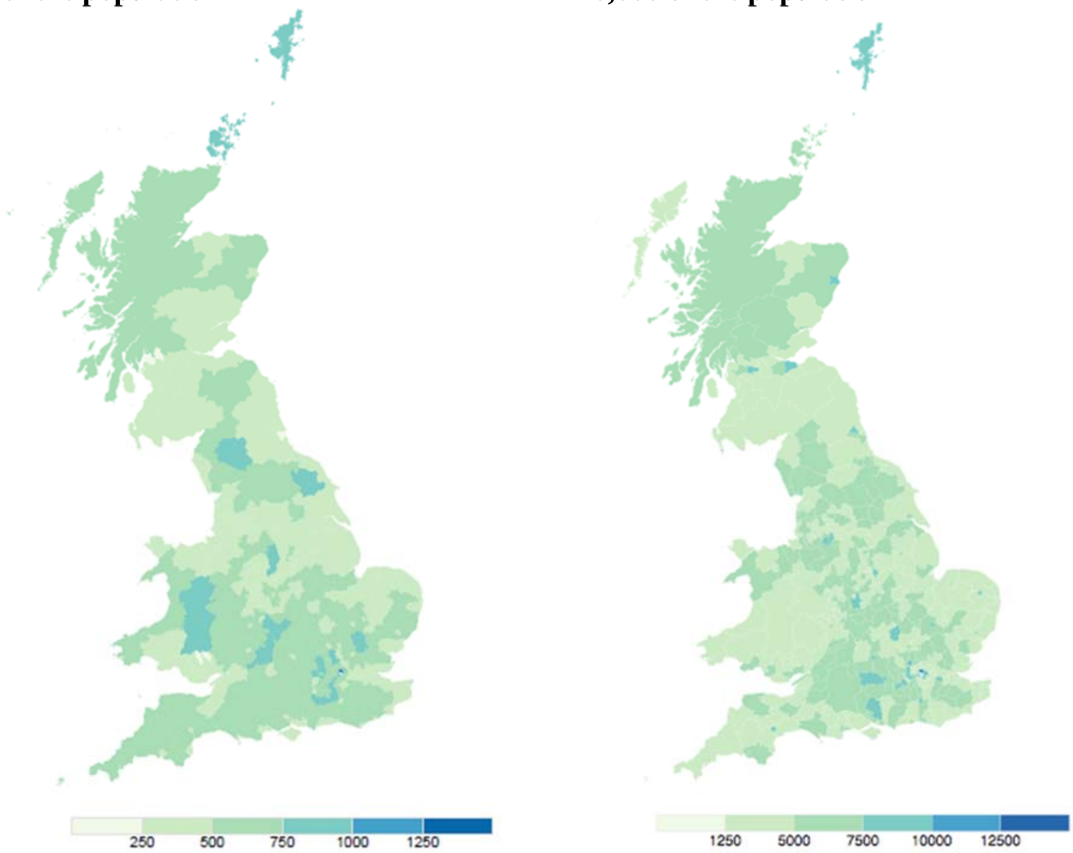
[13] See Nathan and Overman (2013).

[14] The location quotient for industry i in region r is $LQ_{ir} = \frac{\frac{E_{ir}}{E_r}}{\frac{E_i}{E}}$, where E_{ir} are employee jobs in industry i in region r, E_r is the total number of employee jobs in region r, E_i is total employee jobs in industry i and E is the national total of employee jobs. A firms based LQ can be calculated by substituting employment with the number of firms.

sector, this is calculated as the sum of the squared shares of that sector's national employment in each region. The index takes a value of 1 where all employment is concentrated in one region.[15]

Figure 4.2.1: Businesses and employment

A: Local authority businesses per 10,000 of the population **B: Local authority employment per 10,000 of the population**



NOTES: Business Counts (2016) and employment (2015), per 10,000 local population aged 16+ at local authority level. Business data for "local units". Source: IDBR, BRES, APS (ONS).

Facts and maps

The most comprehensive data for understanding the population of businesses in the UK is BEIS BPE, as this includes unregistered, non-employing businesses which tend to be sole proprietors and sometimes partnerships. In the latest data, it was estimated that there were 3 million such businesses in the UK, which together with the registered population of around 2.5 million puts the total number of businesses in the UK at 5.5 million. However, the data on unregistered businesses are not reliable at geographical

[15] The HHI for a given industry (i) is given by $HHI_i = \sum_{r=1}^{R} S_r^2$. Where S_r is the share of national employment in that sector in region r, and R is the total number of regions. When all the employment for that industry is concentrated in one region, the HHI takes a value of 1. When employment is evenly spread across region, HHI takes a value of $\frac{1}{R}$.

levels more disaggregated than the UK "region" (e.g. North East or London), so it is preferable to use IDBR based data on the population of registered businesses when considering the measures above. Because we are looking at local business activity, plants or "local units" are more relevant than business enterprises or "reporting units".[16]

Figure 4.2.1 plots firms and employment per 10,000 working-age population. Panel A shows that there are some local authorities with over 1,000 plants per 10,000, or 1 for every 10 people. Some of these are rural locations including mid-Wales, where the density on this measure is driven by a high share of micro businesses (see Fact 2). The areas with the highest employment rates tend to be in London, followed by Cambridge, Aberdeen City and Oxford (Panel B).

Figure 4.2.2: Industrial specalisation: uniform sectors

NOTES: Source: Calculations based on employment data at local authority level, BRES 2015.

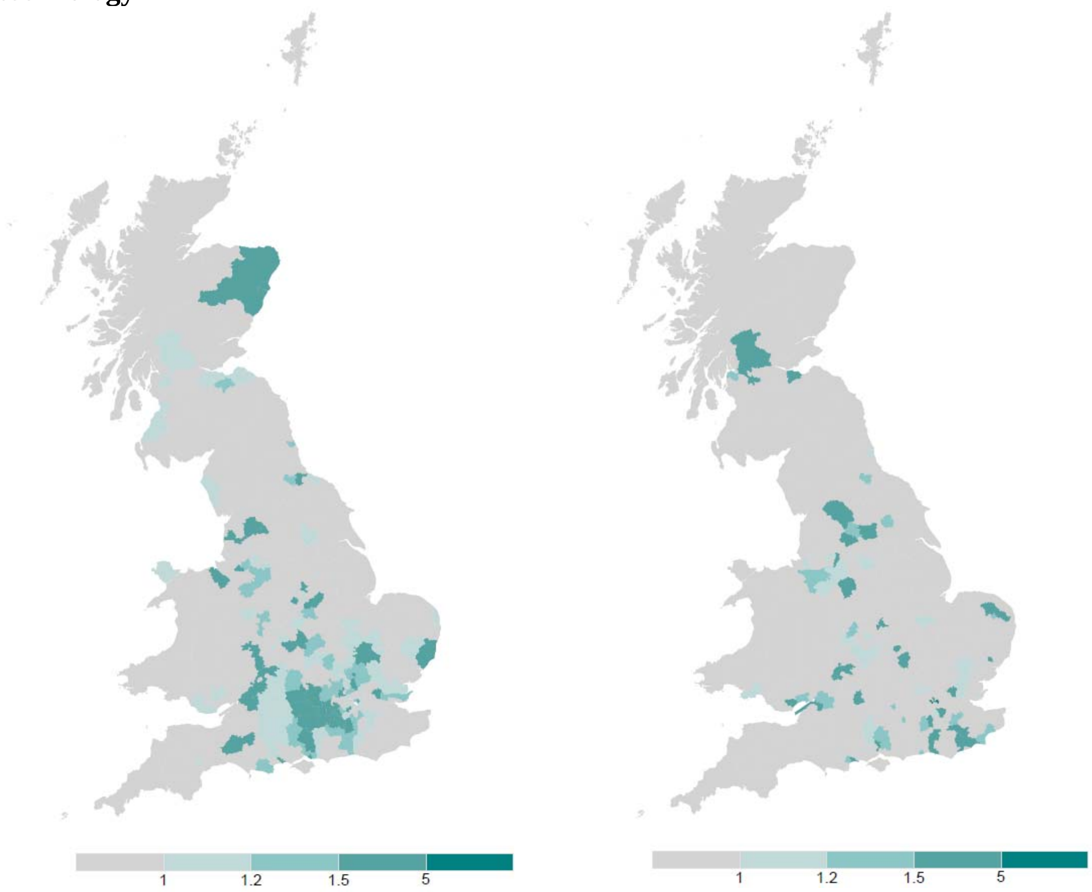
[16] Based upon the IDBR (as extracted from NOMIS), which covers registered businesses only, in 2016, there were 2.5 million reporting units and 3 million local units. The reporting unit and local unit are equivalent for most firms in the UK (around 95% , see discussion at http://doc.ukdataservice.ac.uk/doc/7989/mrdoc/pdf/7989_ardx_userguide.pdf).

Maps of industrial specialisation (LQ) at the broad sector level[17] reveal three distinct patterns. Some industries are evenly spread around the country. In these **uniform** industries there is a similar concentration of firms in all locations.

For many of the industries that follow this pattern a uniform spread is intuitive: often they provide products or services that must be sold locally: for example retail and wholesale trade services have a uniform pattern (Figure 4.2.2, panel A). The sector includes hairdressers, gyms and shops - these are all businesses that are likely to be present in most UK towns. Outside large cities agriculture is spread relatively evenly across the UK (see maps Appendix). More surprisingly, manufacturing is also quite evenly spread across the regions, but is relatively absent in some areas including and around London (Panel B).

Figure 4.2.3: Industrial specialisation: scattered sectors

A. Location quotient: "science and technology" **B. Location quotient: Finance**



NOTES: Source: Calculations based on employment data at local authority level, BRES 2015. "Science and technology" sectors allocated at the 4-digit level.

In some industries, activity is restricted to a number of locations, dotted across the

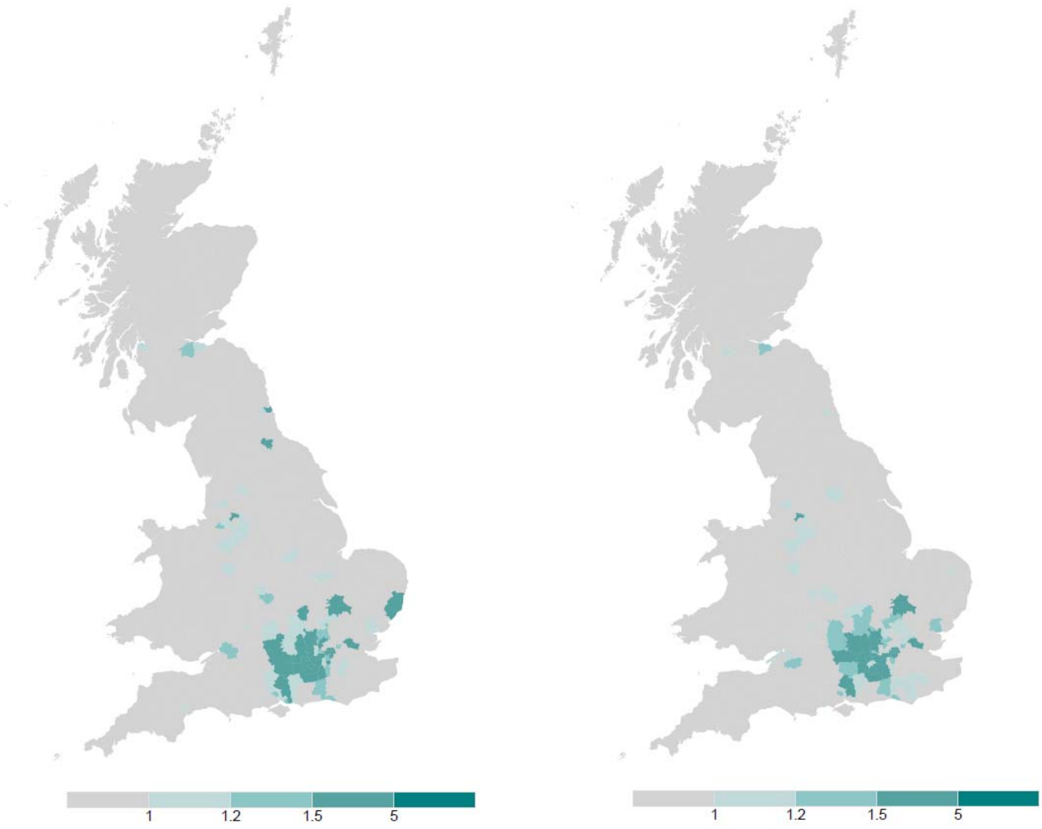
[17] Here we use the standard SIC 2007 "section" level, for an outline of the SIC2007 hierarchy see https://onsdigital.github.io/dp-classification-tools/standard-industrial-classification/ONS_SIC_hierarchy_view.html

country. In these **scattered** industries, the maps show a number of specialist hubs in the UK. This includes firms in "science and technology" sectors[18] (Figure 4.2.3, A), professional, scientific and technical services, and mining and quarrying. The fact that there are over 15 identifiable financial hubs outside London is a challenge to the common belief that banking only occurs in London and the South East (Figure 4.2.3, B).

Some industries have a **single hub**. In these industries, there is only one location with significant activity. The most striking examples are information and communication technology and the "creative" sectors[19]: in both of these areas activity is focused in London and the South East (Figure 4.2.4).

Figure 4.2.4: Industrial specalisation: single hub sectors

A. Location quotient: ICT **B. Location quotient: "creative"**



NOTES: Source: Calculations based on employment data at local authority level, BRES 2015. "Creative" sectors allocated at the 4-digit level.

The maps of the "science and technology" and "creative sectors" are particularly interesting as these are considered to be the key parts of the "knowledge economy".

As discussed, it is also possible to calculate a summary statistic of industrial concen-

[18] We grouped 4-digit SIC codes into "science and technology" sectors using the definition developed by NESTA in Bakhshi et al. (2015), which is based on Eurostat classifications.

[19] Again, as defined by NESTA in Bakhshi et al. (2015). See Chapain et al. (2010) for discussion of creative clusters and innovation.

tration, by sector. One example is the HHI, which we summarise at the aggregate sector level in Appendix Table 4.C.1. Mining and quarrying is the most concentrated industry, which is unsurprising as these activities are driven by the suitability of the area, chiefly the availability of resources. However, finance and insurance activities and the "creative" sectors also show high levels of geographical concentration. Agglomeration is important for activities with returns to density - be it from access to a common skill pool, shared amenities and supply chains or knowledge spillovers.[20]

However, the aggregate industry level in many cases also masks differences at more detailed aggregations. For example, in finance some parts of the sector are highly concentrated (such as fund management and reinsurance) but there are also much less concentrated subsectors including support activities, leasing and non-life insurance (see Appendix Figure 4.B.1 for HHI across 4 digit subsectors in finance).

4.2.2 Fact 2: Firm Size Distribution

The size distribution of British firms is important because of longstanding differences in the way that the typical firm of various sizes operates. Large firms tend to be more productive as they are able to benefit from economies of scale and economies of scope, and they also tend to be better managed[21], use better technologies and are more likely to export. In general, larger firms invest much more than small ones relative to their size: for example the top 400 firms accounted for approximately £15.7 billion in R&D spend in 2015, 75% of the UK's total. Small firms, on the other hand, tend to be more labour intensive. These differences will tend to mean that a location where there are many small firms may have high employment, but low productivity and low pay. Areas where large firms co-locate may drive investment and productivity.

It is common in the data to consider the following categories:

- **Micro (0-9).** This category includes sole proprietors, partnerships and other firms with a small number of employees. Zero employee businesses make up nearly 80% of this category. Examples of this type of company include tradesmen, and the new on-call service industries in which owners operate a personal services company;

[20] Kline and Moretti (2013) consider the effects of a large-scale regional (largely infrastructure) development programme in the US, and provide evidence of lasting gains in manufacturing due to agglomeration economies which were not present in agriculture. Interestingly, they find that these programmes created a displacement of economic activity, so that there was little gain at the national level. For a review of the research frontier on agglomeration economies using firm level data, see Duranton and Kerr (2015).

[21] See, for example, Bloom et al. (2014*b*) and Awano, Heffernan and Robinson (2017)

this could include Uber and Deliveroo, for example. A large portion (73%) of such businesses are unregistered for PAYE or VAT.

- **Small (10-49)**. This category includes firms with between 10 and 49 employees. While firms of this size are small in employment terms, they can be very large on other measures. Investment firms, for example, will often be in this category but could manage very large balance sheets. Around 4% of UK businesses are classed as "small". In some datasets, micro and small businesses are together classed as "small".

- **Medium (50-249).** There were around 40,000 of these mid-sized firms in 2016 (less than 1% of total firms). As above, these firms could be considered large on other measures. British Land, for example, has fewer than 200 employees, but has a market cap of over £6 billion. As a share of its total business population Britain is sparse in this group relative to Germany, where this stands at 1.8% [22] of total firms and which is famous for its "Mittelstand", the specialist and export oriented medium sized companies.

- **Large (>250).** Firms with over 250 employees are relatively rare - there are around 10,000 of them in the UK on the latest data (0.2% of total firms). They are usually companies, but there are also a small number of partnerships in this size band. Public data show that the top private sector employers are Tesco, Compass Group and Intercontinental hotels - between them these three companies employ over 1m Britons. The sectors that have the highest shares of large firms are mining and quarrying, manufacturing and finance.

Facts and maps

The dominance of small firms applies across the UK. Non-employing and small businesses dominate in all regions making up around 99% of firms (Table 4.2.1). This share has risen in recent years, driven by the rise in self-employment and zero employee businesses which has been the most rapidly increasing category of firm (Appendix Figure 4.B.2).

Turning now to the *private sector* (for which detailed firm size splits are available in the BPE and therefore including unregistered businesses), small firms account for around 99% of firms across sectors (see Appendix Figure 4.B.3), though the split between non employing businesses and those with 1-49 employees varies: accommodation and food

[22] Figure based on calculation using 2015 data on number of businesses by size band from Destatis.

Table 4.2.1: Firms by size band-percentages of total firms by region

Region	None	1-49	50-249	250+
London	78%	21%	0.6%	0.2%
South East	78%	22%	0.5%	0.1%
South West	77%	23%	0.5%	0.1%
East of England	76%	23%	0.6%	0.1%
Wales	76%	24%	0.6%	0.1%
Yorkshire and the Humber	75%	24%	0.7%	0.1%
East Midlands	75%	24%	0.6%	0.1%
North West	75%	25%	0.7%	0.1%
West Midlands	74%	25%	0.7%	0.1%
North East	73%	26%	0.7%	0.1%
Northern Ireland	73%	26%	0.7%	0.1%
Scotland	71%	28%	0.8%	0.2%

NOTES: Source: BPE (2016), total economy.

services has a relatively lower share of non-employing businesses (30%) and a higher share in the 1-49 bracket (68%). In education, 94% of businesses are non-employing-these types of businesses include personal tutors, sport or music instructors or other educational businesses.

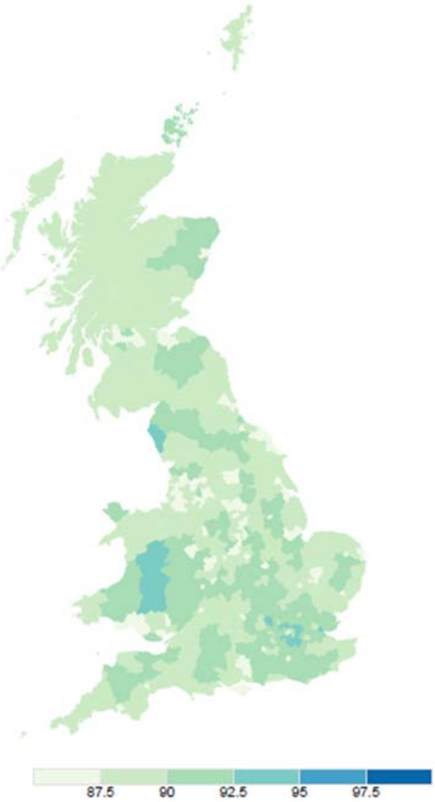
Again, for detailed spatial analysis we use data on local units from the IDBR, which excludes unregistered businesses. We plot maps of the share of local authority firms in different size bands (Figure 4.2.5). This shows that micro-businesses make up a high share of local businesses throughout the UK (panel A), even though unregistered businesses are not included in this map. Small and medium sized businesses (panels B and C) are also quite evenly spread, but large businesses show more of a patchwork (panel D).

Figure 4.2.6 shows that there are a number of local authorities where the share of medium sized businesses has grown. This can be either due to entry of new medium-sized plants, or due to growth in existing businesses - we turn to analysis of firm entry and exit in the next section. Analysis of the distribution of "high growth" firms across space and sectors is an area for future work.[23]

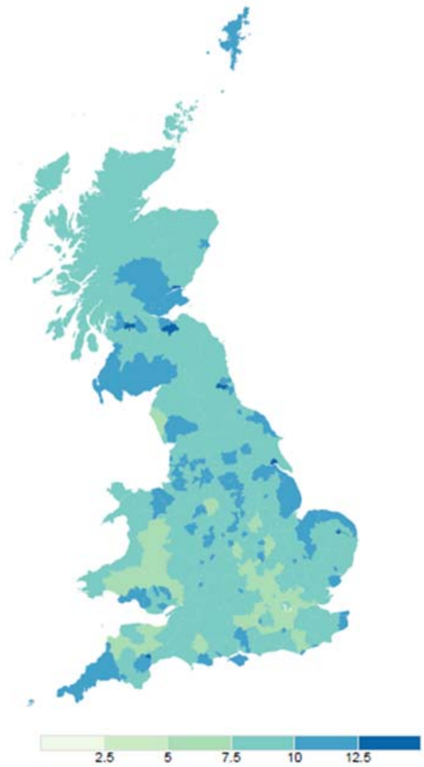
[23] There are a number of different ways to define "high growth" businesses. A common definition is firms that report more than 20% in turnover or employment growth in the most recent year (Brown and Lee, 2014). The OECD classifies businesses as high growth if they have more than 10 employees, and are growing in either turnover or employment at a rate of 20% or higher over three years. Eurostat's definition is the identical but uses a lower threshold of only 10%.

Figure 4.2.5: Share of total firms of different size bands

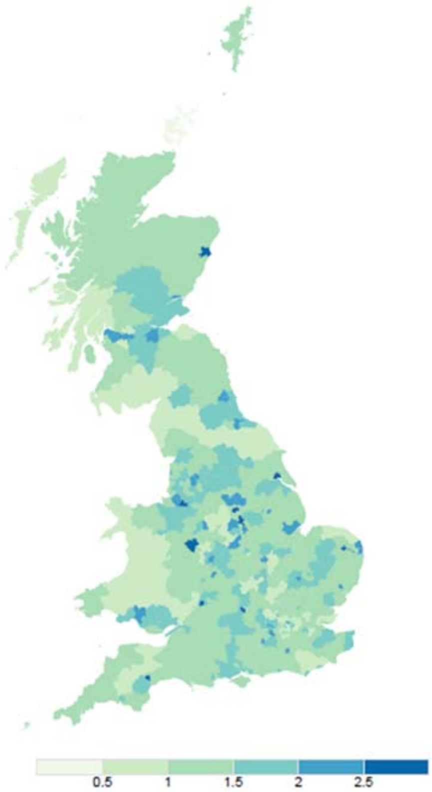
A. Micro (0-9) % total firms



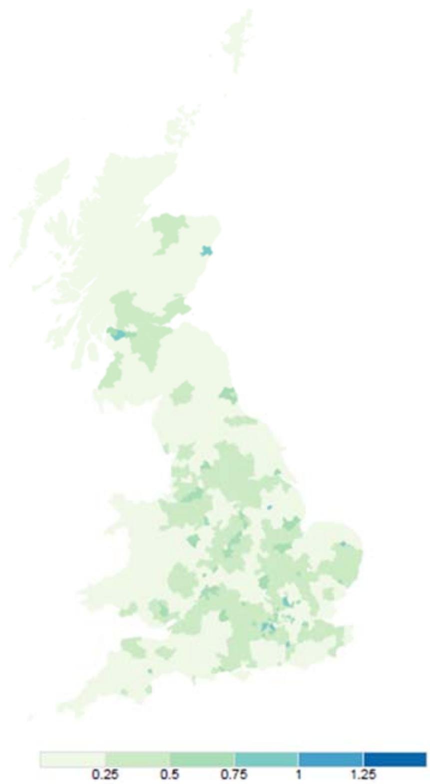
B. Small (10-49) % total firms



C. Medium (50-249) % total firms

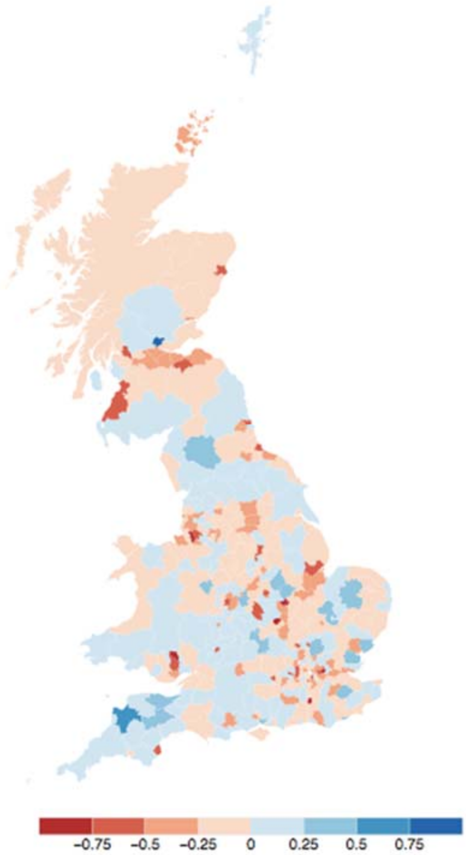


D. Large (>250) % total firms



NOTES: Calculations based on local units at the local authority level (2016), excludes unregistered businesses. Source: IDBR, ONS.

Figure 4.2.6: Medium sized firms, change in local share, 2010-16



NOTES: Calculations based on local units at the local authority level (2016), excludes unregistered businesses. Source: IDBR, ONS.

4.2.3 Fact 3: Business Demography

When headline numbers are used in isolation the number of active firms in an area or category might appear stable. Across the UK, for example, the share of large firms to total private sector firms has remained at around 0.1% since 2000.[24] The stability of such numbers can mask the extent to which business populations are fluid or sticky. One observation made by economists following the 2008 crash was that the number of bankruptcies was surprisingly small. A subsequent worry arose that inefficient or unproductive firms may be hanging on (often aided by their banks).[25] An economy in which this happens risks a kind of economic ossification. The concern, in productivity terms, is that factors of production - everything from bank loans and market capital, workers, and software and patents - could be misallocated or "stuck" in outdated companies, unable to flow to new

[24] Figures for the private sector only, using BEIS BPE which is a consistent source of information for a time series of businesses by size band. Note that figures are rounded.

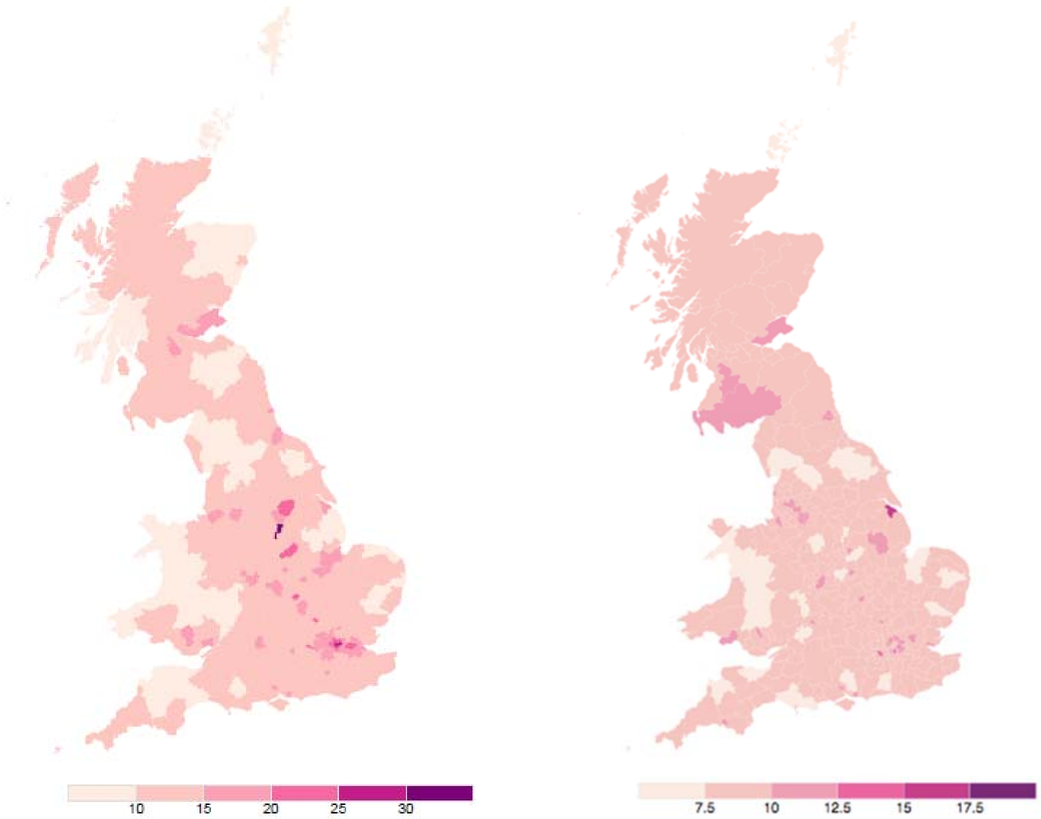
[25] Forbearance refers to the practice of banks granting companies with interest payment holidays. Most analysis to date has estimated a limited impact on productivity.

and innovative ones.[26] Looking at the flow of companies - the extent to which existing companies wind up, and new ones are started up - is one way to examine these concerns.

- **Birth rates**. This is the number of new firms established divided by the existing active business population. "Birth" is defined as an enterprise registering for VAT or PAYE. Active business are defined as those that had either turnover or employment at any time during the reference period.
- **Death rates**. This is the number of firms that go out of business, divided by the active business population at the start of that year. It includes businesses that have ceased trading and are identified as those that deregister for VAT or PAYE.
- **Survival rates**. This is the share of firms that survive for a specified number of years after their "birth".

Figure 4.2.7: Business demography

A. Company birth rates, 2015 (%) **B. Company death rates, 2015 (%)**



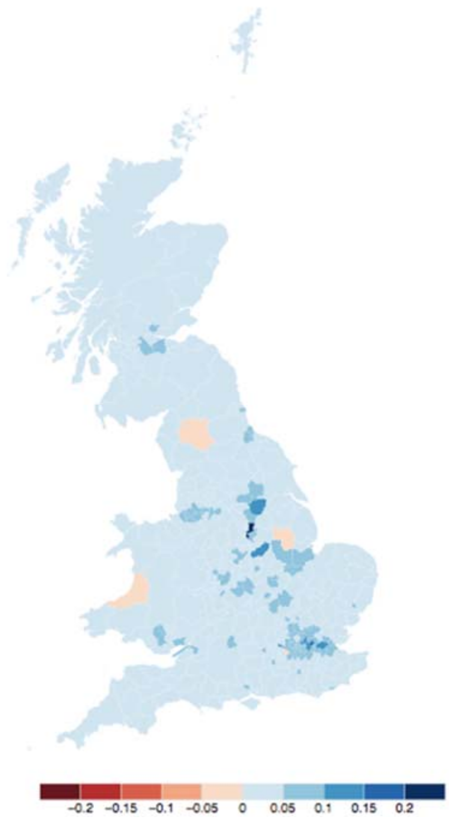
NOTES: Company births as % of active population and company deaths as % of active population by local authority. Source: ONS Business Demography.

[26] There is a growing body of literature on resource misallocation and productivity in the UK, with a particular focus on capital market frictions, see for example Riley, C. and Young (2015), Barnett et al. (2014) and Besley, Roland and Van Reenen (2017).

Facts and maps

The ONS business demography dataset gives detailed breakdowns of company births, deaths, active enterprises and survival rates, and also includes data for Northern Ireland in its aggregates. Across the UK, there were 383,000 company births in 2015, 252,000 deaths and 2.6 million active enterprises. The birth rate is therefore higher than the death rate (at 14% versus 9% respectively). The number of births has exceeded the number of deaths since 2011: as birth rates have grown steadily in all regions and death rates fallen after an initial rise to 2012 following the financial crisis.[27]

Figure 4.2.8: Net rate of change in number of businesses, 2015



NOTES: Calculations based on company births and deaths by local authority. Source: ONS Business Demography.

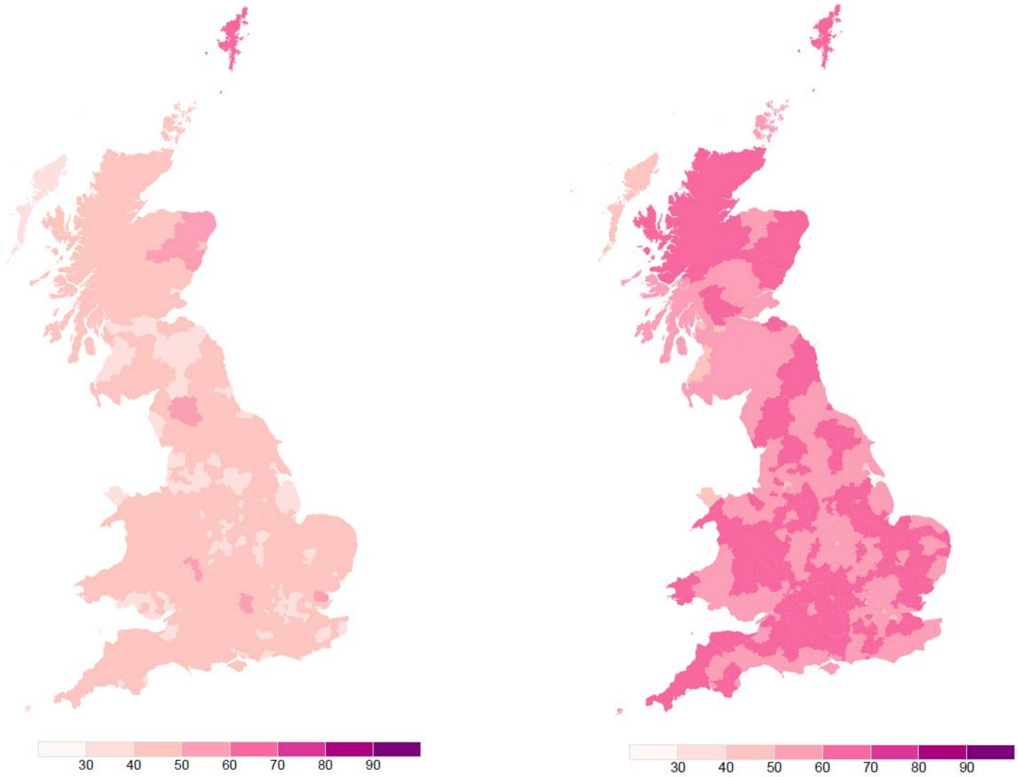
Figure 4.2.7 shows that most local authorities in Britain have birth rates over 10% . In some areas, such as Bolsover, Barking and Dagenham and Newham, over 25% of active businesses were registered in the previous year. Conversely, Figure 4.2.7 shows that for most of Great Britain, death rates are below 10% , and peaks are close to this with 17% in North East Lincolnshire and 14% in Spelthorne and Lambeth being the three highest

[27] ONS analysis at the Local Enterprise Partnership level using data from 2004-2011 showed that the financial crisis had a negative effect on birth rates, and positive effect on death rates, but that effect on death rates was slower to materialise.

values.

Figure 4.2.9: Survival rates

A. 5-year survival rates (%) **B. 3-year survival rates (%)**



NOTES: 5 year and 3 year survival rates, % of companies that started up in 2010, by local authority. Source: ONS Business Demography.

However, in all three of these birth rates outstrip death rates, meaning the number of businesses in these local authority areas grew overall. In fact, there are only two areas where business numbers are in decline - North Kesteven and Eden. This is in stark contrast to figures for 2010, when 285 areas registered a decline (Figure 4.2.8). Yet, overall, these maps reveal that firm "births" and "deaths" are spread relatively evenly across the UK, and therefore do not appear to be a key explanatory factor of spatial differences in performance.

This does not change when we consider 3 and 5-year survival rates. Figure 4.2.9 shows that 5-year survival rates are quite evenly spread, but there appears to be a pattern of lower 3-year survival rates in coastal areas, in particular in the South West, North East and West of England (Figure 4.2.9).

4.2.4 Fact 4: The Spread of Productivity

It is well known that UK average productivity levels lag our main comparators (in the latest data, UK productivity was around 30 percentage points lower than that in France and the US, and 36 percentage points less than in Germany) but this overall headline masks significant variation across space. There is large variation in performance across the regions of the UK, but there is also substantial variation within regions. These differences are longstanding, and there has been little progress towards reducing them despite a number of policy initiatives over the years.[28] Understanding these patterns and the reasons underlying them is crucial for policy makers developing an industrial strategy for the UK.

At its most basic, productivity gives a measure of output produced per unit of input, and labour productivity is the most common measure of this type. The standard measure of output is "Gross Value Added", this is the value of goods and services produced in an area. It is calculated as output minus intermediate consumption. Dividing GVA by the number of workers, or the total hours worked, gives two alternative measures of labour productivity. GVA per hour is more directly comparable as workers in different regions or sectors might work different hours on average. In some cases, GVA per worker is easier to calculate as it requires employment data (which are recorded in the BRES firm level survey data or the IBDR), rather than additional estimates of average hours worked (which tend to be based on Labour Force Survey or Annual Population Survey data).

The ONS produces regional and sub-regional estimates of productivity that are as consistent as possible with the national accounts. It is important to note that such measures are produced on a nominal basis only and do not correct for differences in prices between different areas of the UK. [29]

Facts and maps

Figure 4.2.10 illustrates the spatial variation in GVA per hour for NUTS3 regions - which are equivalent to counties, unitary authorities or districts. At the bottom of the productivity scale is "West Wales and the Valleys"; an area with little industry and agriculture as the main employer. Here, productivity is 21 percentage points lower than the UK average.

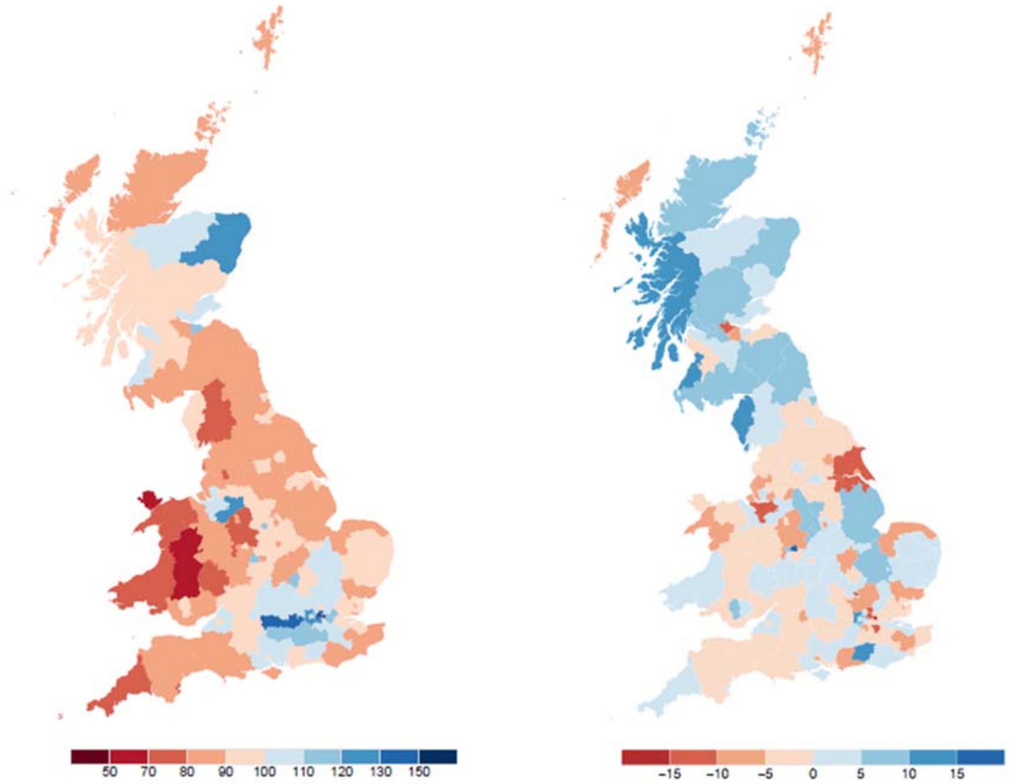
At the other end of the scale there are three high-productivity hubs: the oil industry

[28] For recent discussion, see Overman (2017).

[29] The ONS are working on producing productivity data using the "production approach" which does correct for differences in regional prices.

Figure 4.2.10: Productivity

A. GVA per hour (UK average=100) **B. GVA per hour % change (2008-2015)**



NOTES: Note: GVA per hour at NUTS3 level in 2015, with UK average set to 100 (index), and change over time. Source: ABS, ONS.

around Aberdeen, the area around Greater Manchester and a band of productivity in the South. Contrary to popular belief the high productivity of London does not spread into the South East but rather spreads west along the M4 to commuter towns like Reading and Slough. Productivity in London overall is 30 percentage points higher than the UK average, the figure for "Inner London-West" is 45 percentage points and this the highest productivity sub-region in the UK. Figure 4.2.10 shows that the situation of many of the low productivity regions (most of Wales and the North of England) in 2015 has worsened over time.

The ONS has recently published some analysis of productivity distributions within sectors and regions.[30] This is based on the ABS, and therefore excludes certain sectors and unregistered businesses.[31] This analysis shows that there is a wider dispersion in high overall productivity regions like London and the South East than in lower productivity regions like Wales and the North East (Appendix Figure 4.B.4). London shows the highest

[30] ONS (2017*b*)

[31] The ABS excludes agriculture, finance, the public sector.

dispersion and also a higher proportion of high productivity businesses. Interestingly, this analysis shows that productivity differences between regions are not primarily driven by a different sectoral mix (at least at the broad sector level), but rather differences in productivity within the same sector across regions.[32] For example, London's higher productivity is not simply due to its sectoral make-up, but largely reflects the fact that within certain industries (and particularly in the knowledge intensive service industries) London firms are more productive than firms in the same sector in other regions. We discuss sectoral differences in more depth in the next section.

The types of factor underlying spatial differences in productivity between firms in the same sectors include differences in factor markets (for example access to skills, capital, infrastructure, technology and R&D or management practices) or in product markets (competition, regulation or other factors that affect demand conditions).[33] They could also reflect the differential clustering and associated spillovers. In the UK, recent CBI analysis suggests that the most important factors based on correlations with local area productivity are skills, transport links, management practices and export/innovation intensity (CBI, 2017).

4.2.5 Fact 5: The Leading and Lagging Sectors

Building on the existing sectoral support in the coalition's industrial strategy, the current government's approach is most likely to continue to include a strong element of sectoral support for strong and growing sectors that possess international comparative advantage. It is important to understand which sectors are likely to benefit from government intervention, and also whether there are cases where a broader "missions" approach might be more appropriate.[34] However, consideration of the productivity performance across sectors reveals that some of the sectors with the highest share of employment have particularly low levels of productivity (Figure 4.2.11). Industrial policies specific to these sectors might generate large aggregate gains.

Facts and maps

We begin with a simple aggregate calculation of sectoral GVA per worker. The benefit of this measure is that it can be calculated using ONS GVA and employment aggregates

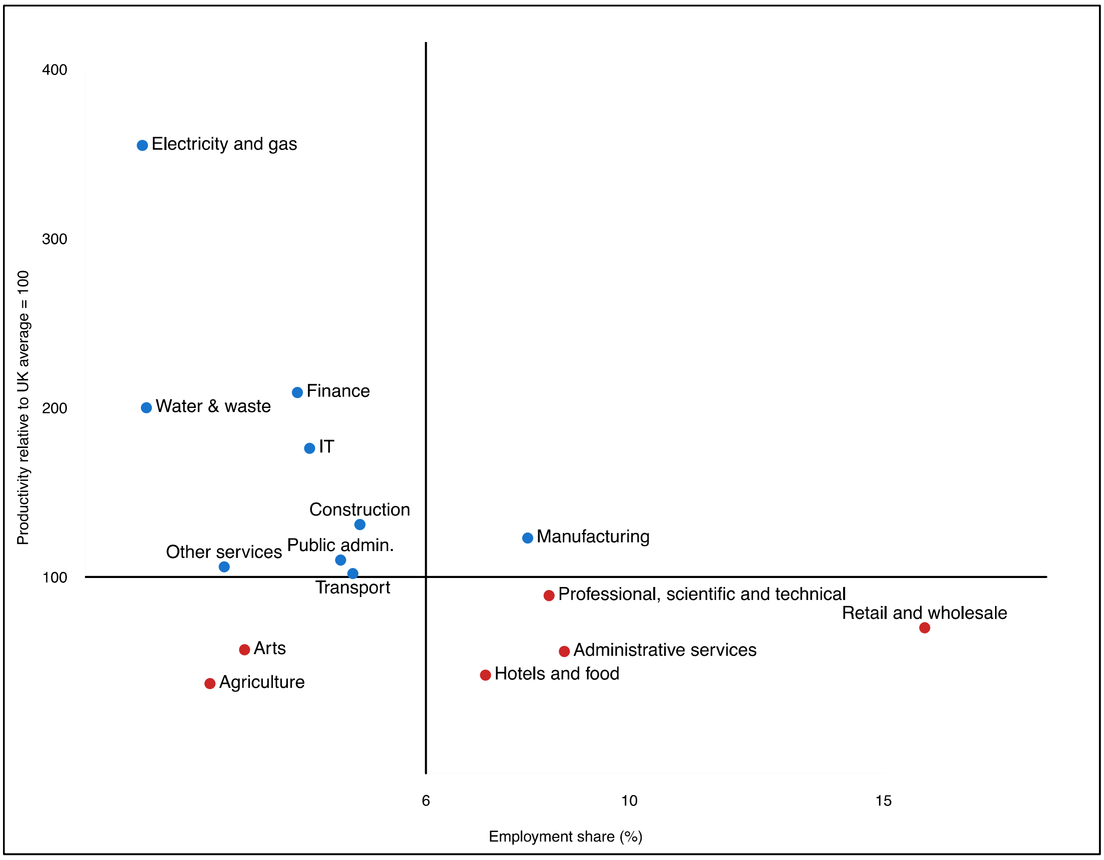
[32] In similar analysis at a more spatially disaggregated level, the CBI also concludes that sectoral mix is not the primary driver of differences in productivity (CBI, 2017), but it does identify some NUTS3 areas that do either appear to lose or gain due to their sectoral mix.

[33] See Syverson (2011) for a review.

[34] See Davis, Martin and Valero (2017) for a response to the government's January 2017 Green Paper on industrial strategy and more discussion on these issues.

for the whole economy including sectors excluded from the ABS (in particular finance, agriculture and the public sector). Figure 4.2.11 plots sectoral productivity relative to the UK average, and also the employment share of each sector. Real estate and mining have very high relative productivities[35] and are excluded from the chart for scaling reasons - but these sectors both have low employment shares (1.8% and 0.2% respectively). Similarly, electricity and gas and water and waste have high productivity but represent a very small employment share in the UK.

Figure 4.2.11: Sectoral productivity relative to average for Great Britain



NOTES: Analysis excludes Northern Ireland (2% of UK GVA) as consistent employment data by sector is not available; non-market economy sectors (education, human health not included on chart). Mining and real estate excluded. Source: ONS GVA income approach - all sectors, and employment from BRES, NOMIS.

High productivity sectors with higher employment shares include finance, ICT, construction and manufacturing. Professional, scientific & technical services is an area where the UK has experienced strong productivity growth in recent years (Appendix Figure 4.B.11), and possesses strong comparative advantage in global trade (see discussion in Fact 7), yet overall its productivity is just below the UK average. This can be explained by the fact that this sector has a high degree of dispersion both within and across regions in

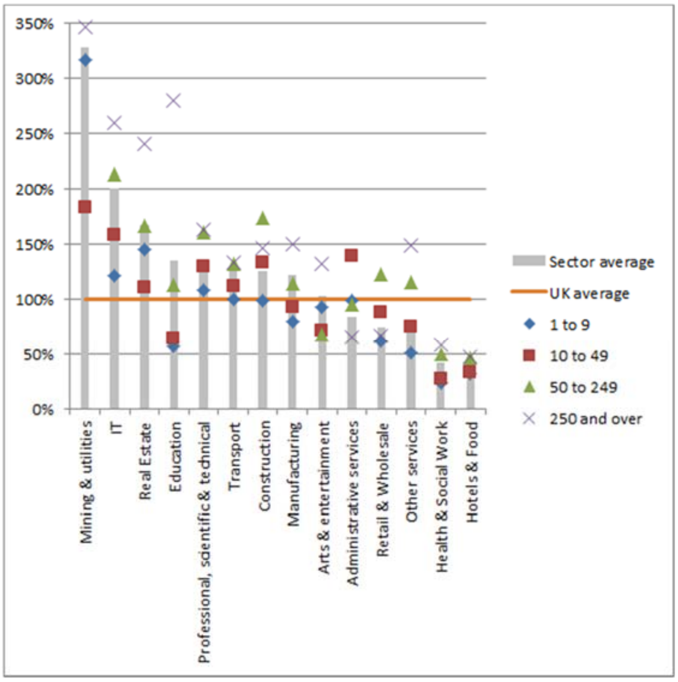
[35] At 726% and 521% of the UK average respectively.

the UK (see discussion below) - there are some very high productivity firms within this sector, but also some less productive firms.

Lower productivity sectors with a high employment share are a particular concern with respect to holding back average UK productivity: these include wholesale and retail trade, accommodation and food and administrative services. These sectors are commonly referred to as "low-wage" or "low-productivity" sectors. Given their high employment share, large aggregate gains could be made by raising their productivity performance: if the productivity in these sectors rose to that of the average UK firm, aggregate productivity would rise by 13%.[36]

It is important for policymakers to understand these differences, since the policy prescriptions for raising productivity in these different types of sector vary. In higher productivity sectors, high-end skills and policies to stimulate innovation are likely to be important. In lower productivity sectors, investment in existing technologies, better management practices, and improved basic or technical skills appear more relevant.[37]

Figure 4.2.12: GVA per worker (2015) relative to UK average, by sector and firm size band



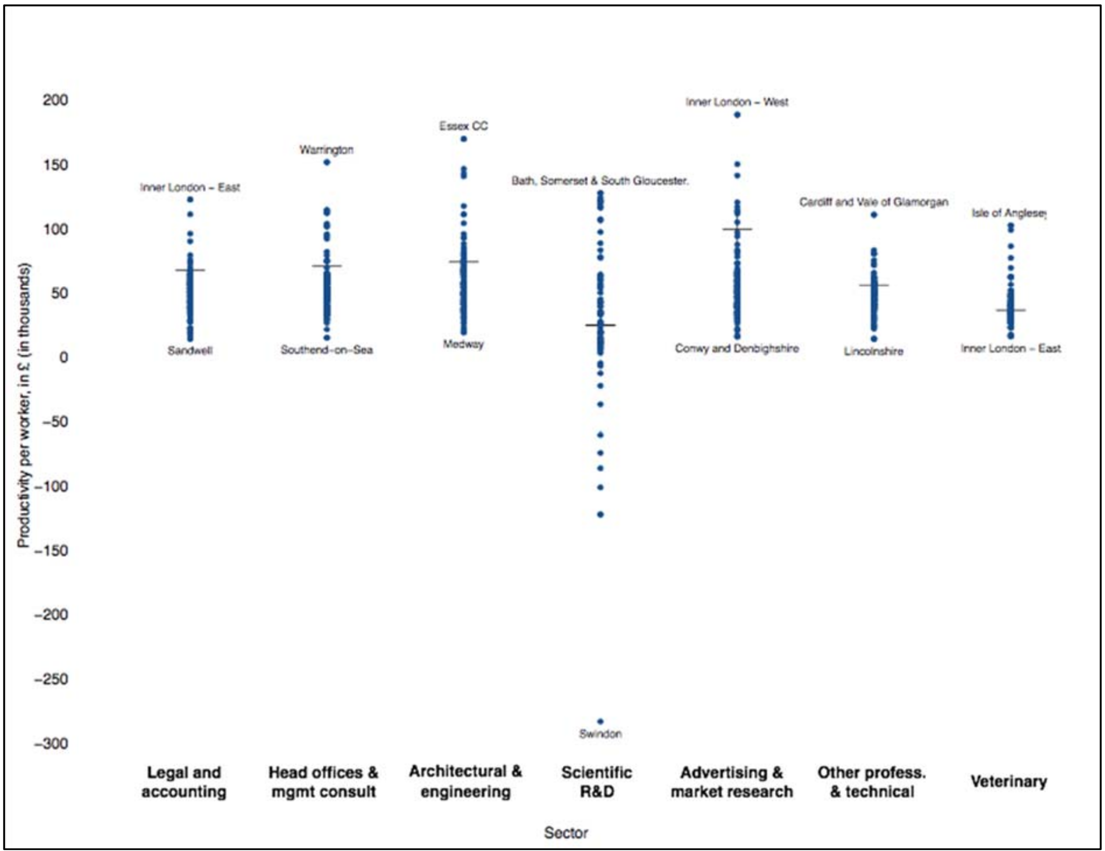
NOTES: Source: ABS, BPE. Indexed to UK overall average. Non-financial business economy (excludes finance, agriculture which has only partial coverage, and public sector). This analysis uses BPE employment for registered businesses only.

[36] This figure is based on a simple calculation whereby the productivity in these three sectors is set at the UK average level, a new total UK GVA is then calculated based on multiplying GVA/worker by the number of workers by sector, and then adding up the sectoral totals. This is then divided by total employment to get the new UK average productivity level.

[37] For more discussion of policy prescriptions for the "low-wage" sectors, see Thompson et al. (2016).

Now focusing on the sectors covered in the ABS, we can look in more detail at productivity by firm size band, and the distribution of firms within sectors. Figure 4.2.12 shows that in most sectors, the smallest firms (those in the 1-9 size bracket[38]) have lower than average productivity. Notable exceptions are administrative services and retail and wholesale trade, where large firms seem to have relatively low productivity on average.

Figure 4.2.13: GVA per worker in professional, scientific and technical services



NOTES: Output per worker at the NUTS3 level, for 2 digit subsectors of the professional, scientific and technical services industry. Source: ABS and BRES, ONS.

More work is needed to understand the dispersion of firms within sectors and regions. Recent ONS analysis has begun to address this. Patterns differ between and across regions between "low" and "high" productivity sectors. In both wholesale and retail trade and accommodation and food service industries, the distribution of firms is quite similar across regions, though London does perform marginally better than other regions (see Appendix Figure 4.B.5). By contrast, in professional, scientific and technical activities, there is a much bigger spread in London (and in other regions too), and median productivity in London is much higher than in other regions (Appendix Figure 4.B.6).

[38] This includes registered non-employing businesses as firms with an employment of 1 - the sole proprietor.

It is useful to consider a more granular disaggregation of sectors to understand what is driving these patterns. As an example, we examine the distribution of NUTS3 regional productivity at the 2-digit level for professional, scientific and technical services (Figure 4.2.13). This shows that the regional dispersion in this sector is in fact driven by scientific research and development, this is likely to reflect the fact that in many cases, and by its nature, the payoffs from investments in R&D are uncertain.

4.2.6 Fact 6: Innovation in the Regions

Innovation is an important source of growth in the long term, and is crucial for enabling certain sectors to stay on the global technology frontier. It is also an area where market failure is well-understood - since innovations tend to generate spillovers which are not always internalised by the firm producing the innovation, the market left to its own devices tends to underinvest in R&D. This is a key justification for government subsidy of innovative activity, and efforts to encourage spillovers. Key measures of innovation include:

- **Research and development (R&D) expenditure.** This is the standard measure of innovation input. Often this is expressed as a share of GDP, to give a measure of R&D intensity. Data are recorded by source of R&D expenditure, often split between government, business or higher education institutions.
- **Patents.** Patents are a standard measure of innovation output. Patent quality can be determined by linking to subsequent citations in future patents or academic papers.
- **Intangible assets.** Traditional measures of innovation do not always capture all the innovative activities of firms, particularly in the service sector. Intangible assets such as branding and organisational practices, together with more traditional R&D, have been shown to be important for a number of sectors. Yet, intangible assets tend to be treated as intermediate consumption, rather than investment in the national accounts, and the UK's investment performance is substantially better once intangibles are accounted for.[39]

Facts and maps

In absolute terms, London and the South East (combined) dominate R&D spending, accounting for nearly a third of total business R&D (Appendix Figure 4.B.7). But over

[39] See, for example, Goodridge, Haskel and Wallis (2014).

20% of UK business R&D is carried out in the East of England, and there it accounts for over 3% of GDP. At a more disaggregated level, Britain's most innovative regions are East Anglia, Cheshire and Herefordshire; reflecting the impact of Cambridge University, chemicals firms located along the River Mersey and a clustering of the life sciences and pharmaceuticals industry in Hertfordshire (Table 4.2.2 and Figure 4.2.14).

We observe a broadly similar pattern across the regions in patents filed to the European Patent Office (EPO) per million of active population (Appendix Figure 4.B.8). London does better on this measure than the previous measure, which looked at only business R&D, reflecting research institutes and universities (both prevalent in London) filing patents. Zooming in further (Figure 4.2.14, panel B), the top five performers are again not surprising. At NUTS 3 level, the top five performers are all well-known, large technology clusters: Cambridgeshire CC (strong in pharmaceuticals and life sciences), Coventry, Oxfordshire (pharmaceuticals, Harwell cluster and UK national research facilities) and Wiltshire CC plus Swindon (home to Intel as well as air and space industry). Areas in England generally do better than areas in Scotland and Wales (four of the five worst performing areas are here, only one is in England).

Table 4.2.2: Business Research and Development as a share of GDP

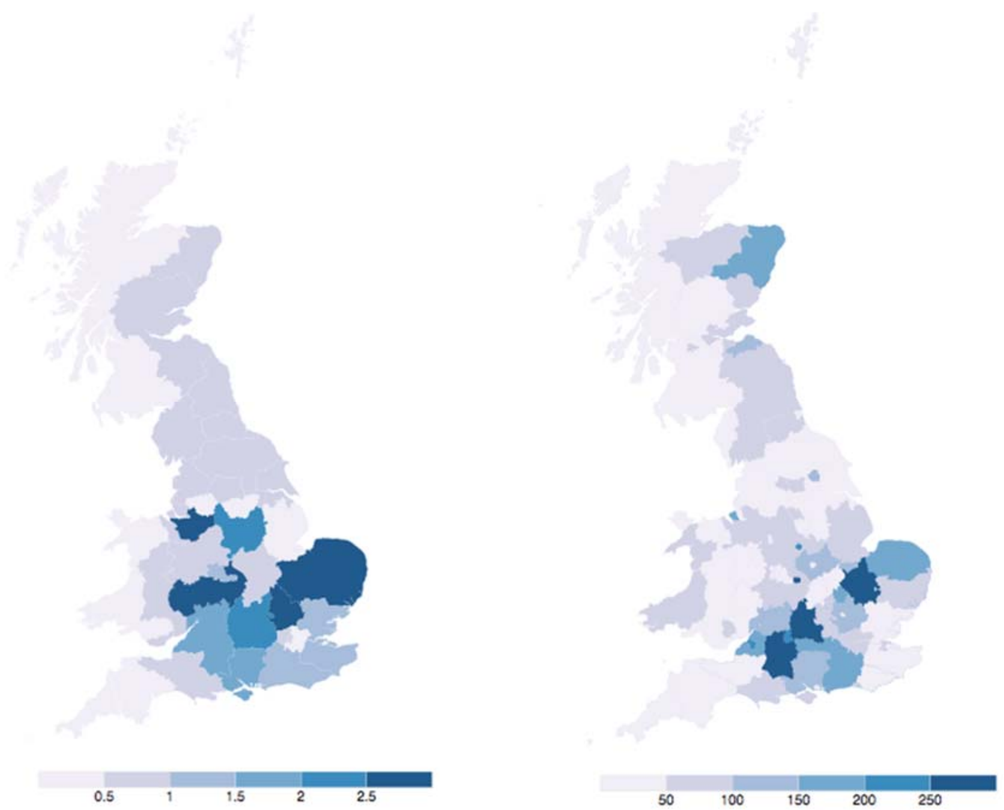
Top 10 NUTS2 regions	%	Bottom 10 NUTS2 regions	%
East Anglia	3.33	South Western Scotland	0.4
Cheshire	3.29	Devon	0.39
Herefordshire, Worcestershire and Warwickshire	3.13	Greater Manchester	0.38
Bedfordshire and Hertfordshire	2.89	South Yorkshire	0.35
Berkshire, Buckinghamshire and Oxfordshire	2.32	Lincolnshire	0.29
Derbyshire and Nottinghamshire	2.19	Highlands and Islands	0.28
Gloucestershire, Wiltshire and Bristol/Bath area	1.81	Inner London - East	0.26
Hampshire and Isle of Wight	1.69	Outer London - South	0.26
Essex	1.48	Cornwall and Isles of Scilly	0.22
West Midlands	1.21	Outer London - East and North East	0.1

NOTES: Total intramural R&D expenditure by business enterprise sector (2014), as a percentage of GDP. Source: Eurostat.

Given the dominance of services in the UK economy, and the fact that traditional measures of R&D fail to account for many of the innovative activities in the service sector, more work is needed to calculate intangibles across space.

Figure 4.2.14: Innovation

A: Business R&D as % GDP **B: Patents per million 16+ population, 2012**



NOTES: Left: Total intramural R&D expenditure (GERD) by sectors of performance and NUTS 2 regions for 2014. Right: Patent applications to the EPO by priority year by NUTS 3 regions for 2012 (latest year available). Source: Eurostat.

4.2.7 Fact 7: Unbalanced Exporting

Exports are an important potential source of growth for businesses. This is not only due to the direct impact of increasing sales through access to new international markets, but also due to the long-run effects of trade on productivity. Trade can have positive effects through increasing competition, making firms seek efficiencies and stimulating innovation.[40] Yet, in aggregate, the UK runs a trade deficit, exporting substantially less than it imports, and this has been the case since the late 1990s. This is largely driven by a trade deficit in goods overall - in fact the UK runs a trade surplus in services, but the volume of services trade is much smaller than that in goods.[41]

The relatively poor aggregate export performance of the UK has long been a concern for policymakers, and today the UK faces significant new risks in this area due to Brexit

[40] See for example, Bloom et al. (2014*a*) or Sampson (2016).
[41] See LSE Growth Commission (LSE, 2017), Chapter 4 for a summary of the UK's trading position.

(discussed in more detail at the end of this section). The EU is the UK's largest trading partner, and reduced access to the Single Market is the likely outcome whatever form Brexit takes.[42]

Research points to a number of factors explaining the UK's existing export shortfall. One explanation is the size distribution of UK firms, as we have seen UK business is dominated by smaller firms but it is larger businesses that are more likely to be exporters. Limited access to finance can hold back exports too. Recent research into what explains firms', propensity to export suggests that financial factors - including the availability of equity finance-play an important role. Exporting can imply fixed start-up costs, meaning that entrepreneurs unable to access capital cannot finance their exports.[43]

It is useful to consider the following measures of export performance:

- **Exporter status.** The ABS is a good source of information on whether or not businesses export, and allows regional, sectoral and size-band analysis of the share of firms that export both goods and services.
- **Export intensities.** The value of exports per worker at a local level can be calculated using regional estimates of goods (obtained from the HMRC regional trade database) and services exports (from ONS experimental export statistics).
- **Revealed comparative advantage.** This is a measure of a country's specialisation in a particular sector in trade. It is calculated by comparing the sector's share in a country's exports to that sector's share in global exports. If the ratio of these two measures is greater than 1, a country is said to have a revealed comparative advantage in a sector. It is useful to bear RCA in mind when assessing the share of firms in different sectors that engage in export activity.

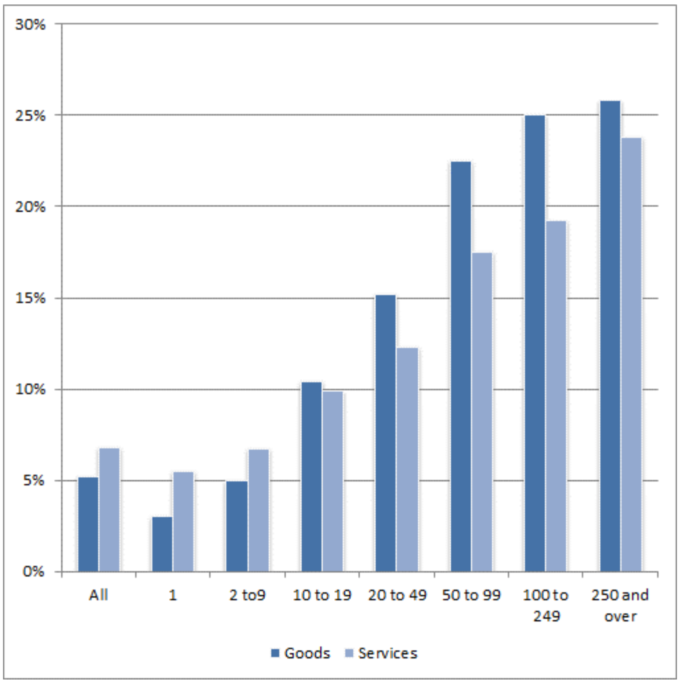
Facts and maps

Figure 4.2.15 illustrates the stark relationship between firm size and export activity. This is actually more pronounced for goods than for services, but in both cases, the share of business exporting increases as firm size increases.

Spatial patterns of exporting are uneven at the regional level (Figure 4.2.16). London and the South East host the highest number of exporting firms, and they represent around 12% of total firms in both regions. The lowest share of exporting firms for any region stands at fewer than 6% in Wales, only marginally higher than in the North East.

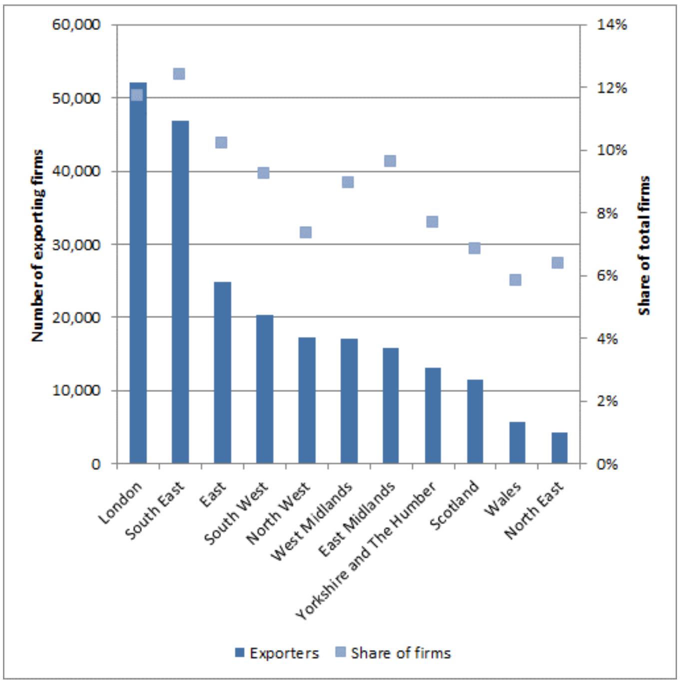
[42] See the CEP's Brexit analysis, collated at http://cep.lse.ac.uk/pubs/download/brexit08_book.pdf
[43] See Manova (2013) and Chaney (2016).

Figure 4.2.15: Exporters by size band, per cent of total firms (2015)



NOTES: Source: ABS, ONS.

Figure 4.2.16: Regional exporters



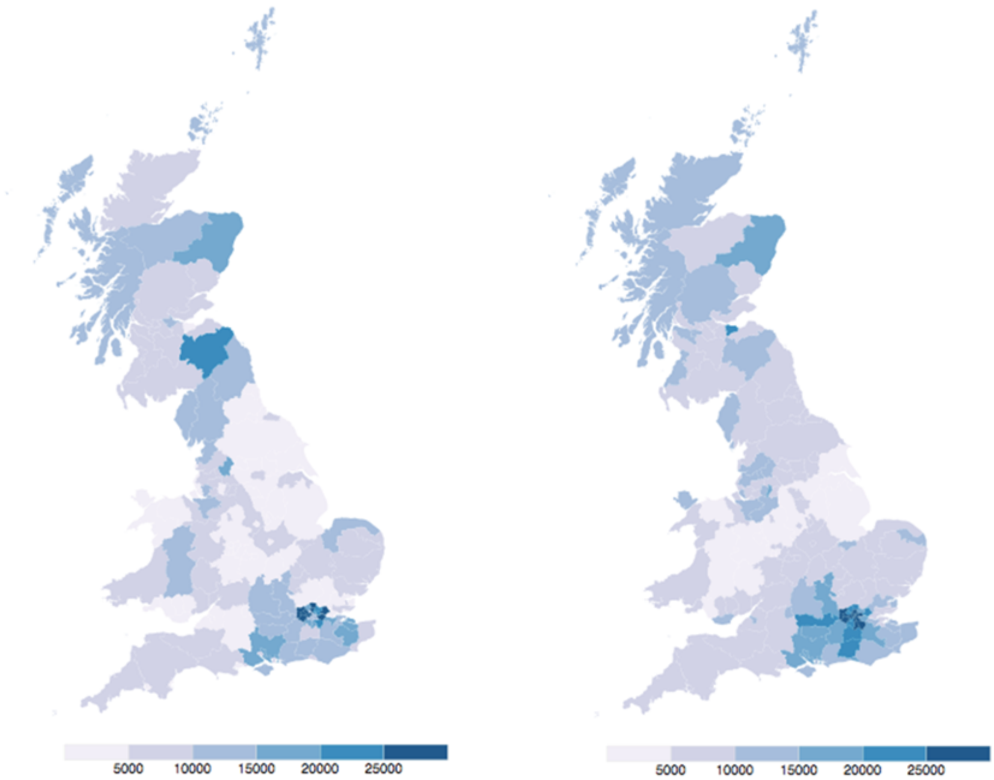
NOTES: Notes: Exporters of goods and/or services total count and as a share of total reporting units. Source: ABS, IDBR, ONS.

It is also useful to consider a more comparable measure of export activity: export intensity gives the average value of exports per worker. Regional data on total exports are available for goods exports from HMRC's regional goods database and for service exports from the ONS experimental regional statistics for the services trade. We apportion this data to NUTS3 regions, for a more spatially disaggregated picture.[44]

We have seen in Figure 4.2.16 that the North East has a low share of exporting firms. The more granular data on goods (Figure 4.2.17, panel A) also point to the North East performing particularly badly on the export intensity measure - with the exception of Northumberland, which has higher export intensity than the rest of the region. However, we cannot make any inference whether a few or many firms are responsible for this. Generally, areas with higher exports per worker are concentrated in the higher productivity areas of London and the South East and in pockets of Scotland. This concentration is even more pronounced for services exports per worker (4.2.17, panel B).

Figure 4.2.17: Exports per worker

A: Good exports per worker (£) **B: Service exports per worker (£)**



NOTES: Calculations based on HMRC regional goods exports database, ONS service trade experimental statistics, Business and Register Survey. Notes: NUTS1 data apportioned to NUTS3 level based on sectoral employment and export intensities; all data for 2015.

[44] The most granular level export statistics are currently released at the NUTS1 level. We model NUTS3 goods and service exports. For this, we use the existing regional HMRC goods exports statistics and the ONS experimental service exports statistics. Both are at NUTS1 level, splitting exports out by broad sectors. To meaningfully apportion regional exports to NUTS3 regions we obtain, at the two digit level, export intensities from the Input Output tables and employment figures, also at two digit level, for each of the NUTS3 regions. These are used as factors to allocate a share of regional exports to its respective NUTS3 regions.

Examining these two maps further suggests that high export areas are also areas of high productivity. Figure 4.2.18 examines the correlation for service exports (panel A), where it appears strong. For goods exports, however, the relationship is less clear (panel B).

Table 4.2.3 shows that there is also large variation by sector. The sectors are ordered by the share of firms that export goods and/or services. As we would expect, manufacturing has the largest share of goods exporting firms, at around 22%. There are large shares of service exporting firms in mining and quarrying, ICT, arts and entertainment and professional, scientific and technical services. These shares are related to areas where the UK has global comparative advantage. In goods, 18 out of 110 traded sub-sectors have an RCA larger than one; the highest RCA being in Aerospace. In services, RCA is calculated at a more aggregated level; in 5 sectors the UK has an RCA larger than one, including insurance, finance, other business and cultural/recreational services.[45]

Table 4.2.3: Sectoral exporters

Section	Goods and/or services	Goods	Services
Mining & quarrying	27%	9%	18%
Manufacturing	25%	23%	9%
Wholesale & retail, repairs	17%	15%	4%
Information & Communications	14%	3%	13%
Arts & entertainment	14%	3%	12%
Professional, scientific & technical	14%	2%	13%
Water & sewerage	13%	11%	4%
Education	12%	3%	9%
Administrative & support	9%	3%	7%
Transport & storage	6%	2%	5%
Other service	6%	3%	4%
Health & social work	3%	0%	3%
Real estate	3%	0%	2%
Construction	2%	1%	1%
Accommodation & food	1%	0%	1%
Agriculture, forestry & fishing	1%	1%	0%
Electricity & gas	0%	0%	0%

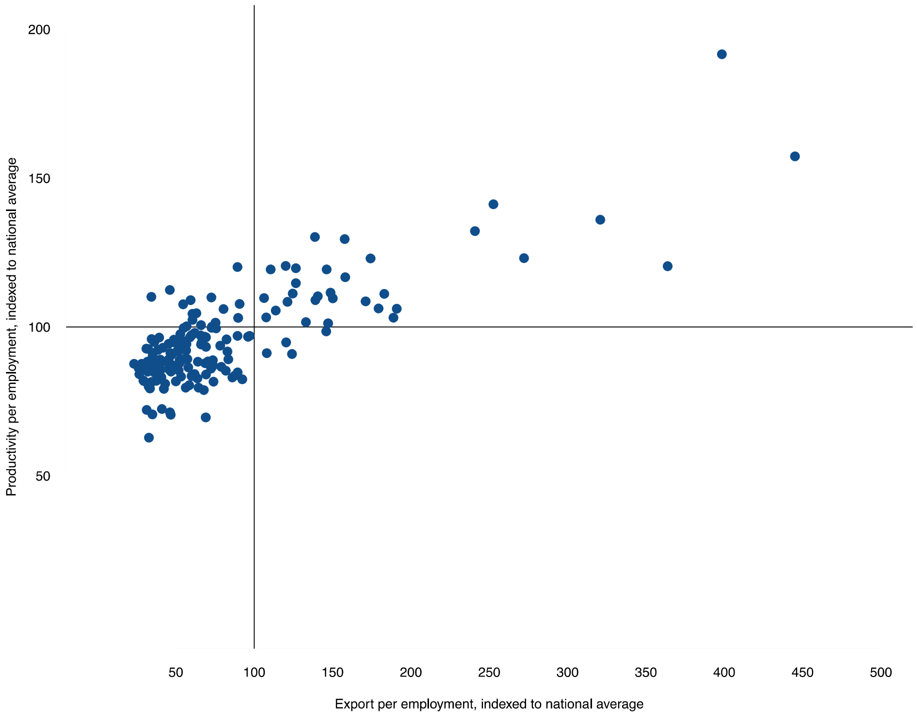
NOTES: Notes: ABS exporters of goods and/or services (2015), ONS. Sectors in order according to overall share of exporters of goods and/or services.

Recent CEP analysis has estimated the local impacts of Brexit due to the increases in trade barriers under differing assumptions for "soft" and "hard" Brexit. Dhingra and Overman (2017) find that all local authorities would see a loss in GVA following Brexit,

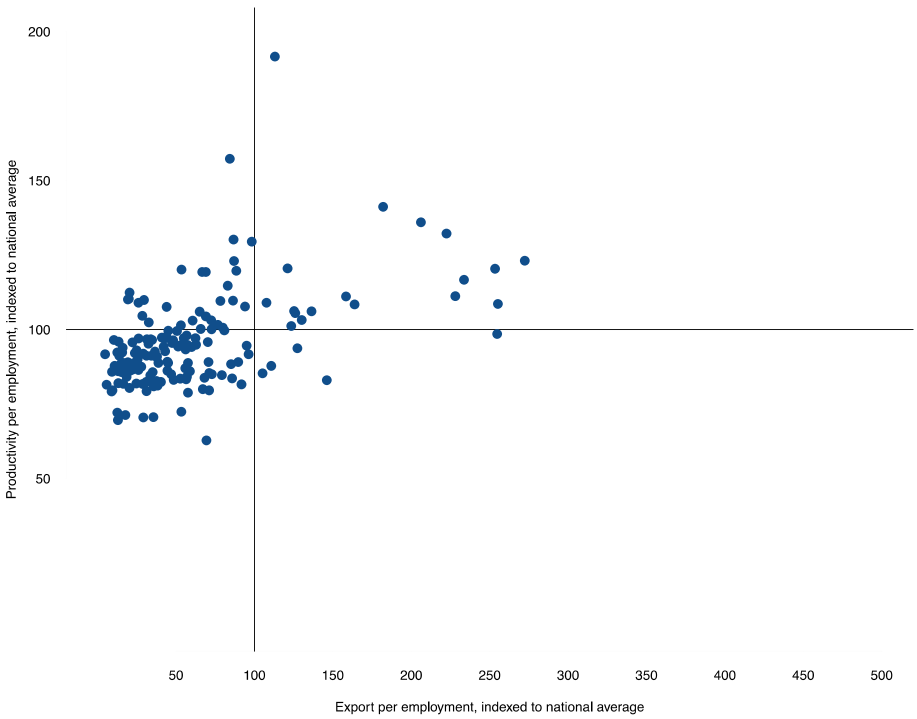
[45] For more detail, see the chapter on "Openness" in the LSE Growth Commission (LSE, 2017).

Figure 4.2.18: Exports and productivity

A. Service exports and productivity



B. Goods exports and productivity



NOTES: Data at NUTS3 level. Sources: ONS service trade experimental statistics, HMRC regional goods exports database, BRES, ONS Regional and Subregional Productivity (Jan 2017). Data for 2015.

but the most affected areas in both scenarios are those in the South of England and urban areas which are specialised in certain sectors where trade with the EU is most prevalent. Specifically, cities that specialise in financial and business services, which are predicted to experience the largest rise in tariff and non-tariff barriers following Brexit. Understanding the local impacts of Brexit through changes to trade, together with immigration, FDI and innovation will be crucial for policymakers developing an industrial strategy with place based elements.

4.2.8 Fact 8: The UK's Coastal Malaise

Regional imbalances are a long-standing weakness of the UK's economy, most prominently those between the North and South.[46] Like the North, the UK's coastal areas have also long been considered to lag behind the more productive Southern mainland but present a different challenge. As a group, coastal areas generally are geographically isolated and have more unbalanced, low skill low productivity economies. They tend to depend on single, and often declining, sectors creating greater exposure to economic shocks in some places (tourism in former seaside towns, but also former agricultural and mining hubs).

Facts and maps

Figure 4.2.19 illustrates the previous point - UK coastal areas are relatively more intense in the accommodation and food service sector than the rest of the country, a sector that is at the core of tourism activities.

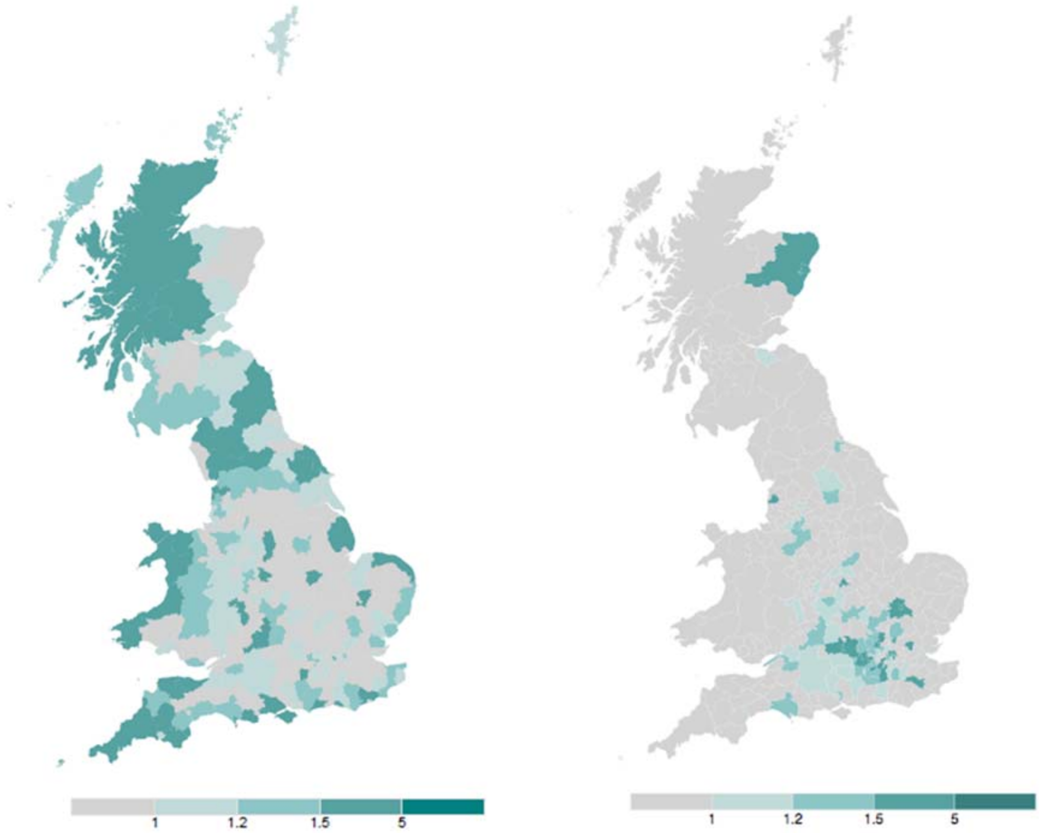
This is also evident in a slightly dated analysis of 121 seaside towns, which provides some evidence that many seaside towns are still almost fully dependent on tourism for employment, with the employment in tourism in 21 towns even at above 50% (Beatty, Fothergill and Gore, 2014). As tourism is a highly seasonal activity, shocks and generally the economic cycle will be felt much more strongly in these areas. While low skill low productivity sectors are large employers, higher productivity sectors are underrepresented, for example the professional, scientific and technical services (Figure 4.2.19, panel B).

Their current low skill base (ONS, 2014) will likely make a move to more productive sectors difficult. At the same time, coastal areas' population dynamics present further challenges to their economies. As illustrated by Figure 4.2.20, mortality rates are much higher in and around the British coasts than inland, in particular the capital region. An older, sicker and more rapidly ageing population will mean rising demand for health

[46] Recent analysis of mortality rates has shown that North-South disparities have risen since the 1990s, see Buchan et al. (2017).

Figure 4.2.19: Specialisation in selected sectors

A. Employment LQ, accommodation and food service **B. Employment LQ, professional, scientific and technical**

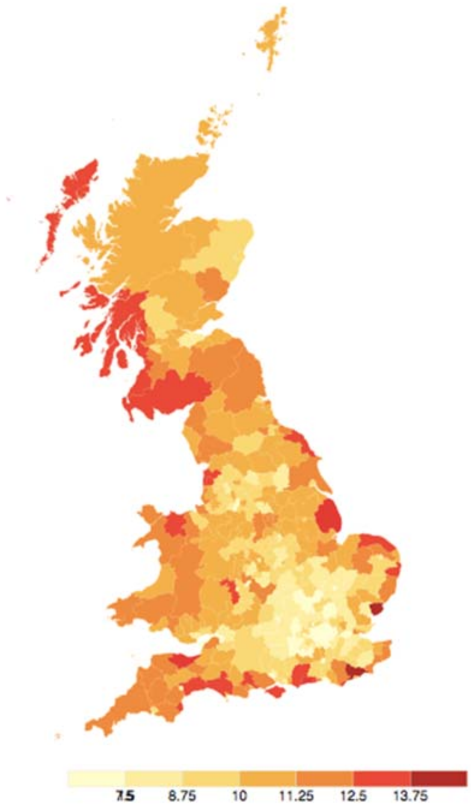


NOTES: Calculations based on employment data at local authority level, BRES 2015.

and care services, a sector already accounting for a large share of employment in many areas, and generally will exert additional strain on local economies and in particular local governments that commission and fund care.

The maps in this section are based on local authorities, which clearly illustrate a difference between coastal and inland areas. However, of the development of industrial policies to address such disparities requires more detailed analysis, with a clear definition of "coastal" versus "inland". Different definitions are currently applied to analysis at the local authority level - from simple distance to the coast measures or grouping all coastal communities with a sea border as coastal if 50% of its population is within 50 kilometres of the sea (used by Eurostat) to highly detailed area classifications used by the ONS in their analysis of census data (ONS, 2014).

Figure 4.2.20: Crude death rate per 1,000



NOTES: ONS, data for 2015.

4.2.9 Fact 9: The Power of a Single Firm

Our "bottom-up" approach to mapping business in the UK produces some striking results. Ribble Valley and Hyndburn appear as a centre for wholesale and retail trade, and Salford appears as an important location for real estate activities outside of London; South Dorset as an important location for finance.

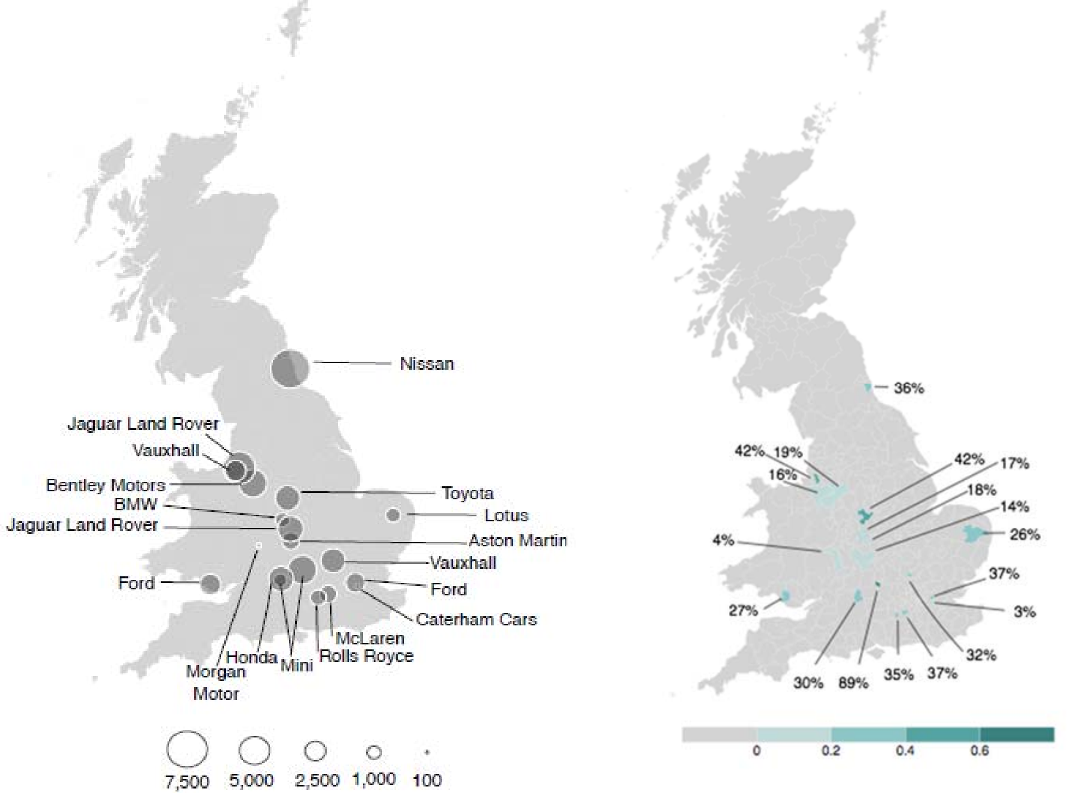
Patches of high productivity in north Lancashire, Derby and Brentwood are influenced by the major plant of BAE Systems, Rolls Royce and Ford, respectively. Further examples are Tata Steel in Port Talbot and Airbus in Broughton (Flintshire), both in Wales. The same can also be true for service sector firms, for example Sky in parts of Scotland.

This also occurs in other European countries. For example, in Germany Volkswagen drives the strong productivity performance of the Wolfsburg area - its residents largely depend on Volkswagen and its suppliers for employment. VW alone employs 60,000, in a city with a working age population of only 77,000. Elsewhere, BMW, which is headquartered in Munich and produces nearby in Milbertshofen, is of lesser importance to the immediate area.

It is reasonable to assume that the smaller the geographic area, the more likely it is that a single firm drives its economic performance. Over and above their direct impact on local GVA, large firms can also generate spillovers.[47] In fact, research based on the US has shown how the performance of single large firms can help explain fluctuations at the national level.[48]

Figure 4.2.21: Car companies and manufacturing employment

A. Car companies, employment **B. Share of manufacturing employment**



NOTES: Source: Car manufacturing plants obtained from SMMT, and employment data from Bureau Van Dijk. Local authority employment from NOMIS. Notes: Two Rolls Royce plants are excluded as they do not manufacture cars but focus on defence and civil engineering.

The implication that individual companies can be hugely important for local or regional economies is clearly a risk - if the company fails the region will be in trouble - but it is also an opportunity and shows that attracting just a few successful companies to a small area can transform its economy.

Facts and maps

The companies mentioned above are all listed companies, and the location of their

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[47] See Greenstone, Hornbeck and Moretti (2010) for evidence that "million dollar" plants generate local spillovers in US counties. Bloom et al (2016) use a similar methodology to find evidence that such plants generate spillovers in terms of better management practices in nearby plants.

[48] See for example Gabaix (2011).

major sites are public knowledge allowing us to map them precisely. Maps can be drawn for any given sector, as an example we choose the car industry.

In Figure 4.2.21A we plot all the 19 car manufacturing plants in Britain, and their employment. Figure 4.2.21B shows their share of local authority manufacturing employment (the underlying data for these charts is summarised in the Appendix (Table 4.C.2)). [49] These data show that Mini's Cowley plant makes up 89% of manufacturing employment in Oxford, though it only represents 3% of total employment (excluding public administration) there. Toyota in South Derbyshire makes up the highest share of total non-public administration employment, at 10%.

4.2.10 Fact 10: The German Benchmark

Germany is an interesting comparator for the UK for a number of reasons. The two economies are neighbours in a global ranking of countries by GDP, ranking 4$^{\text{th}}$ and 5$^{\text{th}}$ respectively. Both have a strong industrial heritage yet have faced economic underperformance with a strong regional dimension: broadly speaking in the UK there has been a division between North and South, whereas in Germany the division is between East and West. Finally, Germany is a good place to examine policy solutions: its economy was seen as the weak link in Europe in the early 2000s, yet since the 2010-12 euro crisis it has outperformed its EU peers, including the UK. In this paper we compare the UK's regional and sectoral productivity and innovation to Germany, similar exercises can be carried out for other comparator countries such as France and the US.

Facts and maps

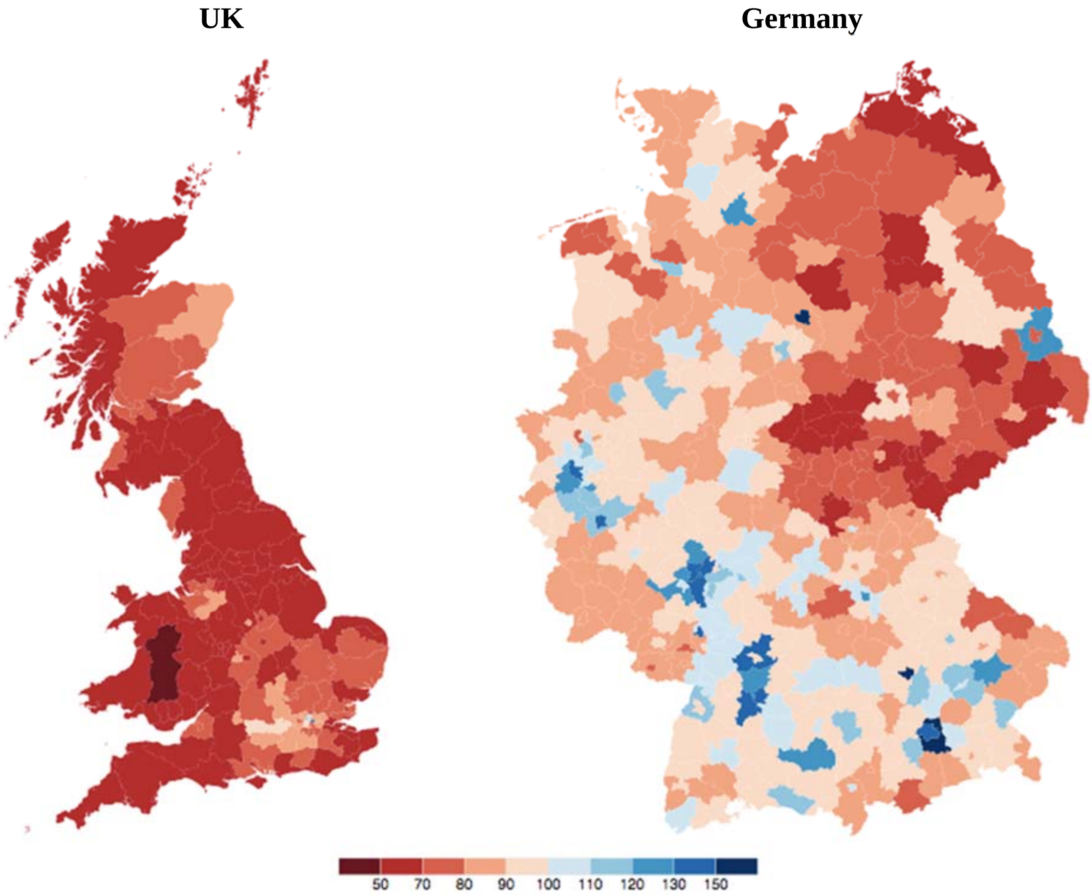
A number of points emerge from a comparison of German and British productivity performance on a geographic level:

- **The aggregate gap:** At an economy-wide level there is a large gap between the UK and Germany. In the latest data, UK GVA per hour is 36 percentage points below that of Germany.[50] Most of Britain's high performing regions (with the only exceptions being in central London) are far behind the German average (Figure 4.2.22). Likely reasons for the aggregate gap include Germany's higher investment in both physical capital and R&D, strong export performance, better quality vocational and technical education and management practices in firms. Since the financial crisis, UK

[49] We map these companies' plants rather than their headquarters, information on which is available from a mix of Bureau van Dijk, company websites and other sources and which we triangulate with each other.
[50] ONS (2017*a*)

productivity performance has been particularly poor and in the latest ONS aggregate data is lower than its pre-crisis level. Comparing the sources of productivity growth pre and post crisis (to 2014) reveals that in Germany, productivity overall, and Total Factor Productivity[51] (TFP) have continued to grow post 2008, while in the UK TFP growth has been negative (see Appendix Figure 4.B.9).

Figure 4.2.22: NUTS3 GVA per hour versus German average (=100)



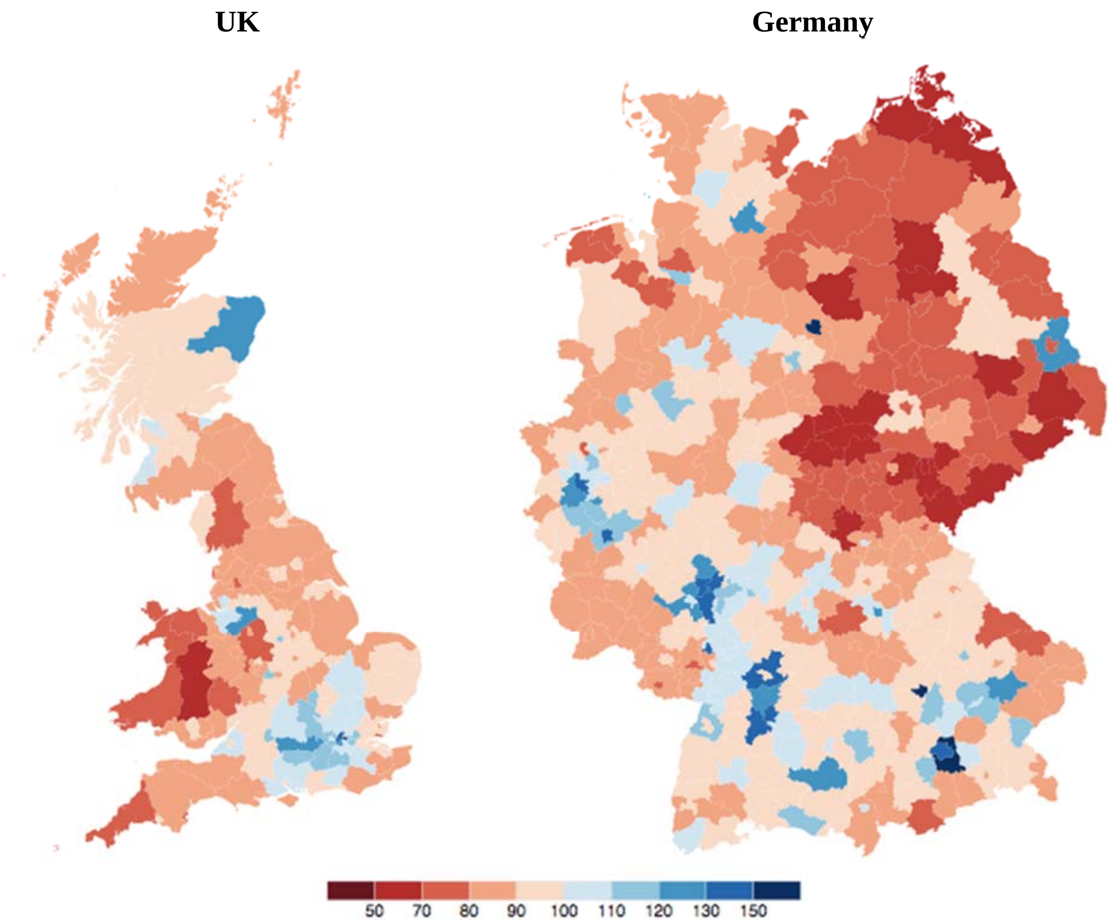
NOTES: GVA per hour at NUTS3 level in 2014, with Germany's overall productivity set to 100 (index). Source: UK data from ONS Regional and Subregional Productivity release (Jan 2017), German data from the federal states national accounts (VGRdL).

- **Germany's regional strengths: multiple productivity hubs.** Germany has many high productivity hubs across the South and West including Bayern, Baden-Württemberg, Hesse and North Rhine-Westphalia. Figure 4.2.23 shows many spots of the highest productivity: many of these are high-productivity areas around German cities including Cologne, Frankfurt, Stuttgart and Munich - and many of these cities are connected by a hinterland that is itself high productivity. By contrast, the UK's high

[51] TFP is the portion of productivity that is unaccounted for by measurable factor inputs such as capital and labour, and reflects the efficiency or intensity with which inputs are used in the production process. It is therefore a measure of technological progress.

productivity regions are few, and are more tightly bunched. The only example of a linking is a high-productivity area that spreads west along the M4 towards Bristol.

Figure 4.2.23: NUTS3 GVA per hour versus national average (=100)



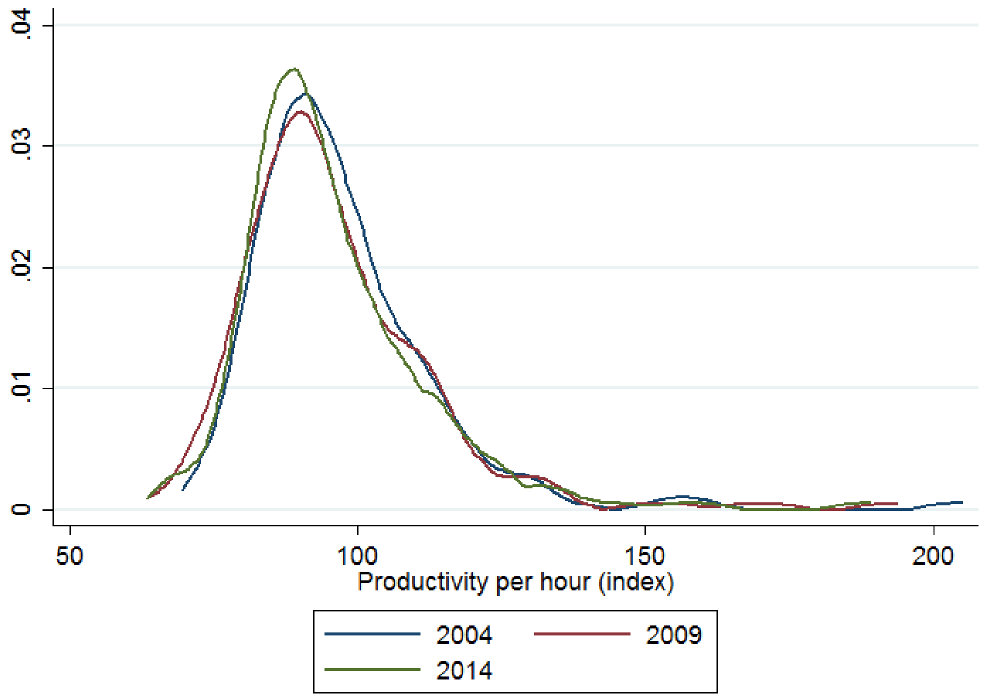
NOTES: GVA per hour at NUTS3 level in 2014, with the overall country's level set to 100 (index). Source: UK data from ONS Regional and Subregional Productivity release (Jan 2017), German data from the federal states national accounts (VGRdL).

- **Germany's regional weaknesses: the east.** A productivity map of Germany suggests that despite its aggregate higher productivity than the UK, the country's regional disparities appear more stark than those in the UK. The German Länder that were part of the German Democratic Republic until 1990 are systematically lower productivity; that this has been identified in Germany as a problem since reunification suggests that regional productivity differences can become entrenched and hard to shift even in strongly performing economies.

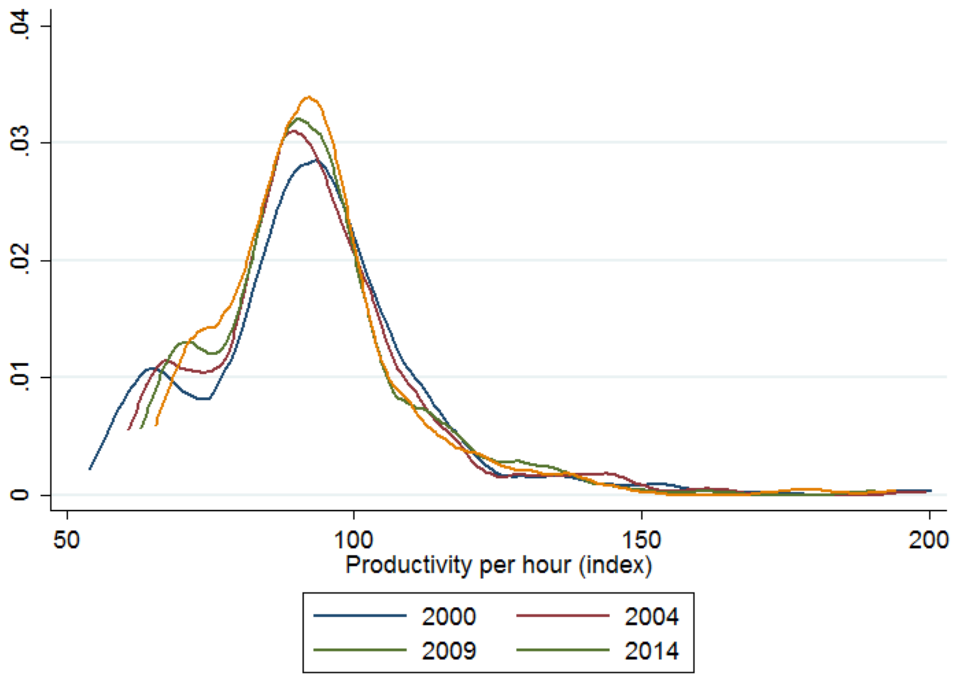
- **Catch up growth:** Between 2000 and 2014 the low-productivity regions in Germany have caught up with better performing ones. This can be seen in Figure 4.2.24 - in 2000 the distribution is "bi-modal" with a peak showing the large number of low

Figure 4.2.24: Distribution of regional productivity

A. Distribution of regional productivity, UK



B. Distribution of regional productivity, Germany

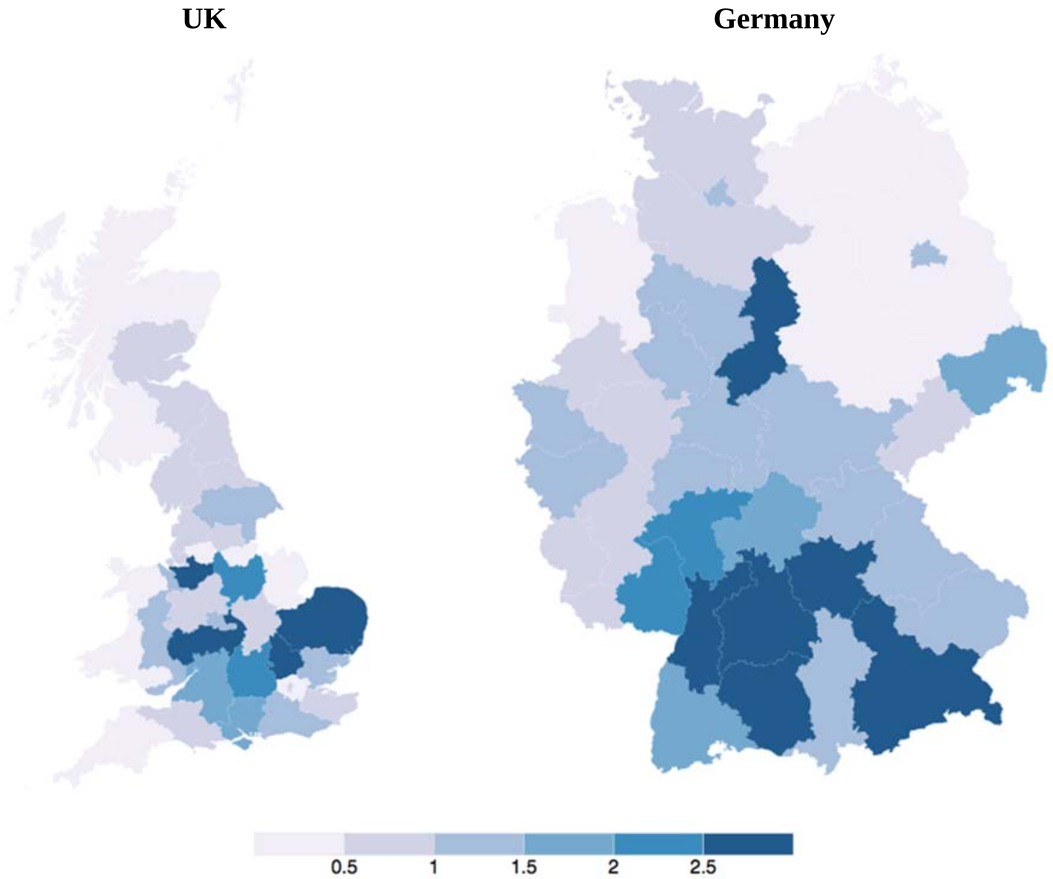


NOTES: Distribution of GVA per hour at NUTS3 level, with the overall country's level set to 100 (index). Source: UK data from ONS release (January 2017), German data from the federal states national accounts (VGRdL).

productivity regions; by 2014 the second peak has disappeared: more regions have caught up with the average region. The UK on the other hand has seen the opposite process and is starting to develop a "thick tail" of poorly performing regions. This suggests that while Germany's lagging regions may be catching up, the UK's are falling behind.

- **Regional innovation**. In 2015, the UK spent 1.7% of GDP on research and development (R&D) while Germany spent close to 3%.[52] Mapping R&D for the UK and Germany (Figure 4.2.25) shows thatthis is more heavily concentrated in the South (in Bavaria and Baden-Württemberg's industrial regions) though Lower-Saxony in the North also has two areas with above 2.5% of GDP spending. All these areas are home to Germany's carmakers as well as other high tech industry.

Figure 4.2.25: Business R&D as a percentage of GDP



NOTES: Total intramural R&D expenditure (GERD) by sectors of performance and NUTS 2 regions. Data for 2013 (latest year where data are available for both countries). Source: Eurostat.

[52] The US also spends closet to 3%; the OECD average is 2.4%. This includes government spending. The portion of R&D that is carried out by businesses shows a similar pattern: UK businesses spend around 1% of GDP on R&D, while German ones (and those in the US) spend close to 2%.

- **Gaps across the sectors.** The productivity gap exists in most sectors when the UK is compared against Germany (Appendix Figure 4.B.10), the only exceptions are mining and finance. The service sectors have driven productivity growth in the UK both before the financial crisis and since, whereas manufacturing has been more important in Germany (Appendix Figure 4.B.11). Productivity growth in professional, scientific, technical and administrative services has held up relatively well a pattern that differentiates the UK from Germany where productivity in these sectors has fallen.

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4.A Data Appendix

In this paper we provide a geographic view of British business performance. We use what we consider to be the best available data in each map and chart. There are a number of official sources available and navigating them can be confusing and time consuming. Given the rising interest in UK corporate performance and location across Whitehall and the fact that the ONS is reviewing the way it collects economic data, this section provides a brief overview of the available data and its strengths and weaknesses.

Access to data varies considerably by dataset. First, high-level summaries are available in ONS or other government publications. Often the accompanying spreadsheets to these give more detail, and the ONS also publishes extra analysis in user requests. Second, detailed statistics with more granular breakdowns can be accessed via "NOMIS" (the ONS service for detailed UK labour market statistics). Third, it is also possible to work with the underlying microdata (administrative or survey data) in a secure environment.[53] Where possible in this paper we use disaggregated summary statistics released by the ONS, as this has the advantage that the data have been prepared in a way that is consistent with ONS methods for the National Accounts.

Table 4.A.1 summarises the features of key datasets which are useful for understanding British business. An underlying source of business data is the Inter-Departmental Business Register (IDBR). This is a live record of VAT or PAYE registered businesses. Firm-level data, ("microdata") can be accessed via the Business Structure Database (BSD) which gives an annual snapshot of the IDBR, and detailed summary statistics are available in NOMIS. The IDBR provides information on location, industry, employment, turnover, foreign ownership, legal status, birth and death of the business. Data are divided into "local units" (the plant) and "enterprises" (the overall business organisation, many of which consist of more than one plant or business site).

The ONS publishes two main annual reports based on IDBR data: "UK Business: Activity, size and location", and the "Business Demography". Detailed summary statistics are made available on the ONS website or NOMIS. "UK Business: Activity, size and location" is useful for geographical analysis, since it gives data on local units or plants as well as information at the "reporting unit" business level. The "BIS Business Population Estimates" is another source which includes an estimate of the unregistered business

[53] Either the ONS Virtual Microdata Laboratory (VML) - a physical location where researchers can work on the data, or the UK Data Service secure lab, a service that allows researchers to work in a separate desktop on their own approved computer.

population, obtained by combining IDBR data with the ONS Labour Force Survey and HMRC self-assessment tax data.[54]

The IDBR provides the population of firms from which samples are chosen for business survey data. The largest business survey in the UK is the "Annual Business Survey" (ABS), which covers the production, construction, distribution and service industries representing approximately two thirds of the UK economy and contributes to the UK's National Accounts. Financial and other business data are collected in this survey at the reporting unit level, and for geographic analysis needs to be apportioned to local units. The ONS releases a number of annual publications based on the ABS (for example "ABS: UK non-financial business economy statistical bulletins" or "ABS: Exporters and Importers in Great Britain") and other resources and summary statistics, often at highly disaggregated levels.

The microdata are also accessible in the VML or secure lab, and the names of the related datasets have changed over the years. The ABS has been carried out since 2008 and includes only financial data: including variables on turnover, gross value added and investment. It is supplemented with employment survey data from the "Business Register and Employment Survey" (BRES, see below for more detail). The predecessor to the ABS, the "Annual Business Inquiry" (ABI) included an employment survey and was used to create the "Annual Respondents Database" (ARD). Recently, the ONS has developed the "ARDx" combining the ABI (1998-2008) and ABS (2009-2015).[55] Microdata for Northern Ireland are not available.

BRES is the official source of employee and employment estimates by detailed geography and industry, and gives a broader sector coverage than ABS. The BRES sample does not include Northern Ireland, and the UK data archive does not hold equivalent employment data for Northern Ireland. While the ONS conducts other surveys of employment (such as the "Labour Force Survey"), BRES is the recommended source for detailed analysis of geography and industry. BRES summary statistics are available in NOMIS. While discussion of wages is outside the scope of this paper, we note that the Annual Survey of Hours and Earnings (ASHE) is a panel survey of hours of work and wages collected from businesses (rather than individuals, as is the case in the Labour Force Survey). This data can be combined with other business microdata using IDBR reference

[54] For more detailed discussion comparing sources for business population and demographics see https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/16418/guide_to_the_uk_business_pop

[55] For a description of the ARDx, see http://doc.ukdataservice.ac.uk/doc/7989/mrdoc/pdf/7989_ardx_userguide.pdf

numbers.

The "UK Innovation Survey" (UKIS) provides the main source of information on business innovation in the UK, and also represents the UK's contribution to the Europe-wide "Community Innovation Survey" (CIS). BIS produces a regular publication summarising the data, and detailed statistics are available in Eurostat at NUTS2 level, and the microdata can also be accessed.

There are also a number of data sources which are useful for considering particular parts of the economy or specific measures of business performance. Orbis is an important source of financial information on companies in the UK (and worldwide), but only covers the subset of larger firms that are required to file company accounts. In addition, since 2011 researchers have been able to gain access to HMRC administrative tax return data, via the HMRC Datalab. This contains all information disclosed on tax returns (including turnover, and investment), but not variables such as employment. There are currently restrictions over the extent to which these data can be merged with other secured datasets.

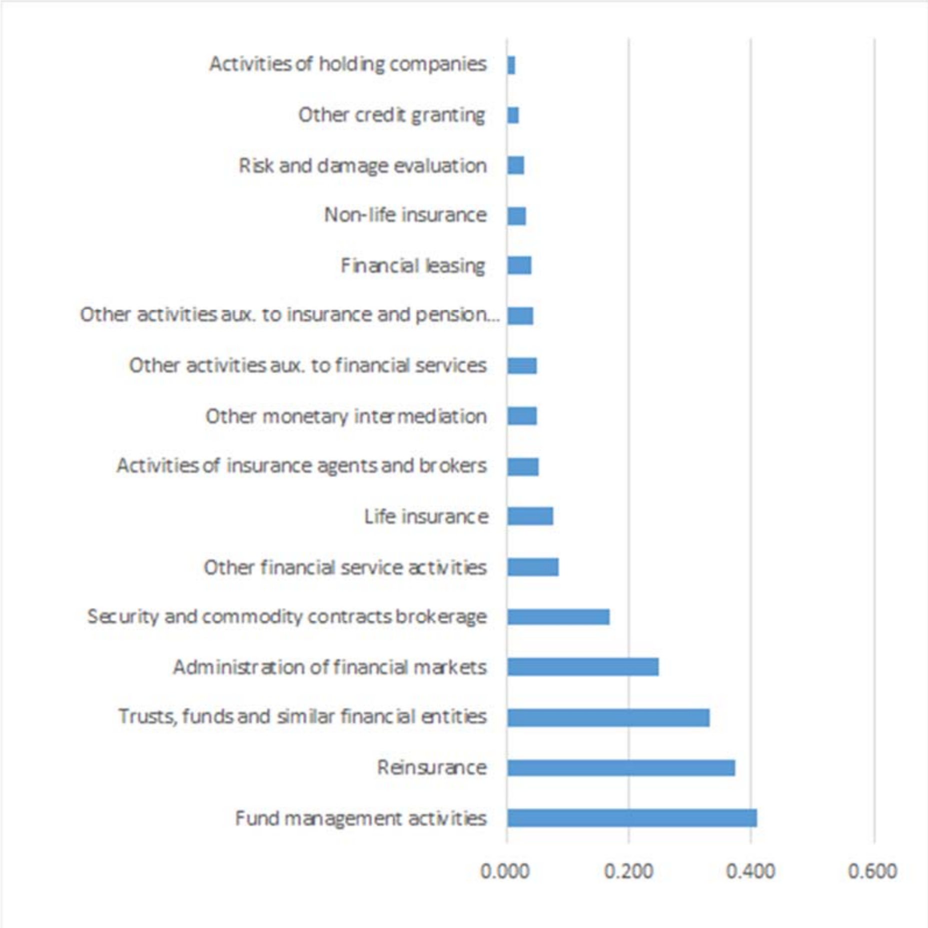
Disaggregated data on the value of exports can be obtained for goods and services separately. The HMRC regional trade in goods statistics which gives detail on the value of exports/imports and counts of exporters/importers, together with trading partners by region. The ONS "International Trade in Services" dataset does similar for service sectors company trade, and the ONS has recently released some experimental estimates regionalising the value of service (sub-) sector exports.

Table 4.A.1: Key datasets on UK business giving sectoral or regional disaggregation

Dataset (underlying source)	Coverage	Key measures	How to obtain?
ONS statistics on population of registered businesses (Inter-Departmental Business Register-IDBR)	VAT and/or PAYE registered businesses and local units	Activity, size, location, legal status, births, deaths, survival	Detailed stats: NOMIS (2010-2016) Key publications: "UK Business: Activity, size and location" and "ONS Business Demography" Summary stats and user requests alongside annual publications Microdata: Annual extract of IDBR in the Business Structure Database (BSD), UK data service secure access (1997-2016)
BIS Business Population Estimates - BPE (IDBR, ONS LFS, HMRC self-assessment tax data)	VAT and/or PAYE registered businesses plus estimate of unregistered businesses.	Activity, size, location. Employment and turnover summarised by size bands.	Summary stats alongside annual publication
ONS Business Demography (Inter-Departmental Business Register-IDBR)	VAT and/or PAYE registered businesses and local units.	Births and deaths, "active" population	Summary stats and user requests alongside annual publication Microdata: Annual extract of IDBR in the Business Structure Database (BSD), UK data service secure access (1997-2016)
Annual Business Survey - ABS	Largest business survey in the UK, conducted annually. IDBR is the sampling frame. Data collected for reporting unit. Covers the non-financial business economy.	GVA, turnover, employment costs, the value of purchases of goods, materials and services, exporting status.	Summary stats and user requests alongside annual publication Microdata: ABS (previously Annual Respondents Database - ARD) available in the UK data service secure access (1997-2015). ARDx newly collated dataset for period 1998-2015.
Business Register and Employment Survey - BRES	Official source of employee and employment estimates by detailed geography and industry. Broader sector coverage than ABS.	Employment/employee data is available by mode (part/full-time) and gender.	Detailed stats: NOMIS Summary stats and user requests alongside annual publication Microdata: UK data service (2009-2015)
UK Innovation Survey - UKIS	Main source of business innovation data in UK, UK contribution to the EU Community Innovation Survey	Innovation activity, type of innovation, context and general economic information.	Summary statistics available in Eurostat at NUTS2 level. Microdata: UK data service secure access (1994-2014) Regular publication: BIS UK Innovation Survey
Orbis (Bureau Van Dijk)	Firms that file company accounts (worldwide coverage). Generally missing information on smaller firms.	Financial, operational and governance information.	Licence required, access via "end user interface".

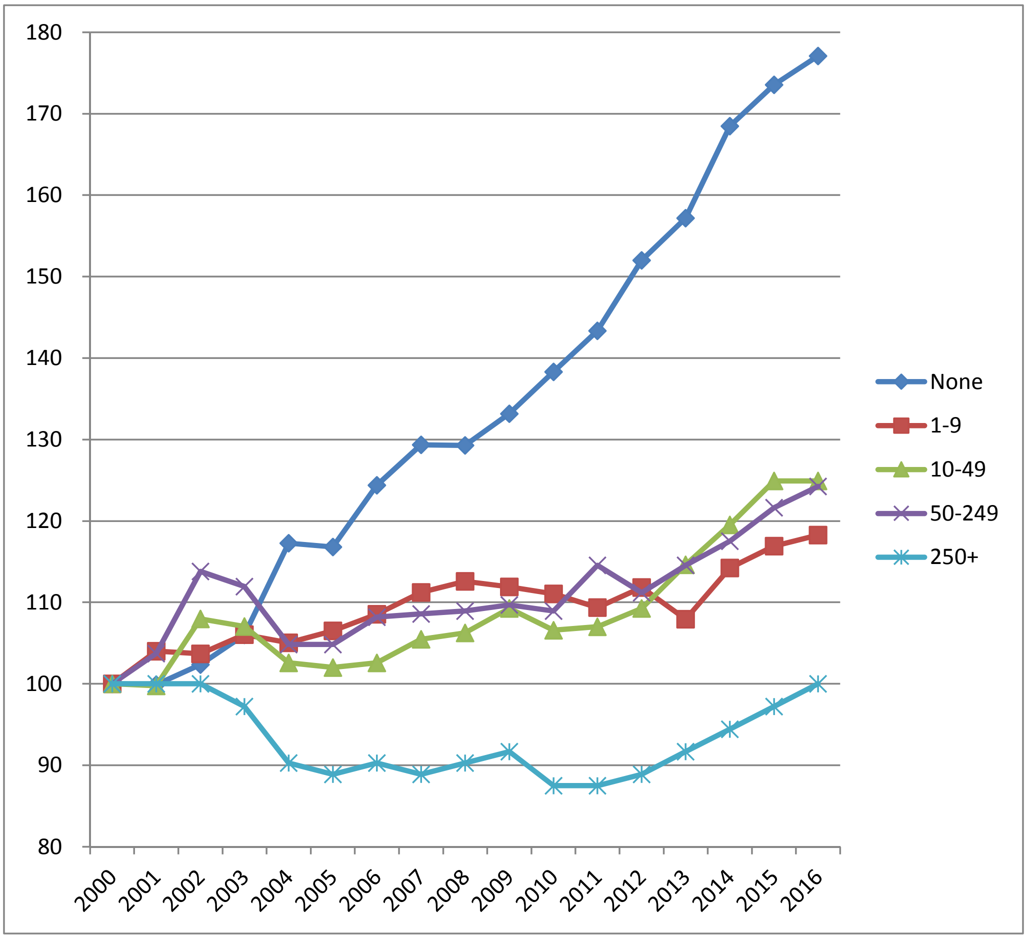
4.B Appendix Figures

Figure 4.B.1: HHI (employment), finance subsectors



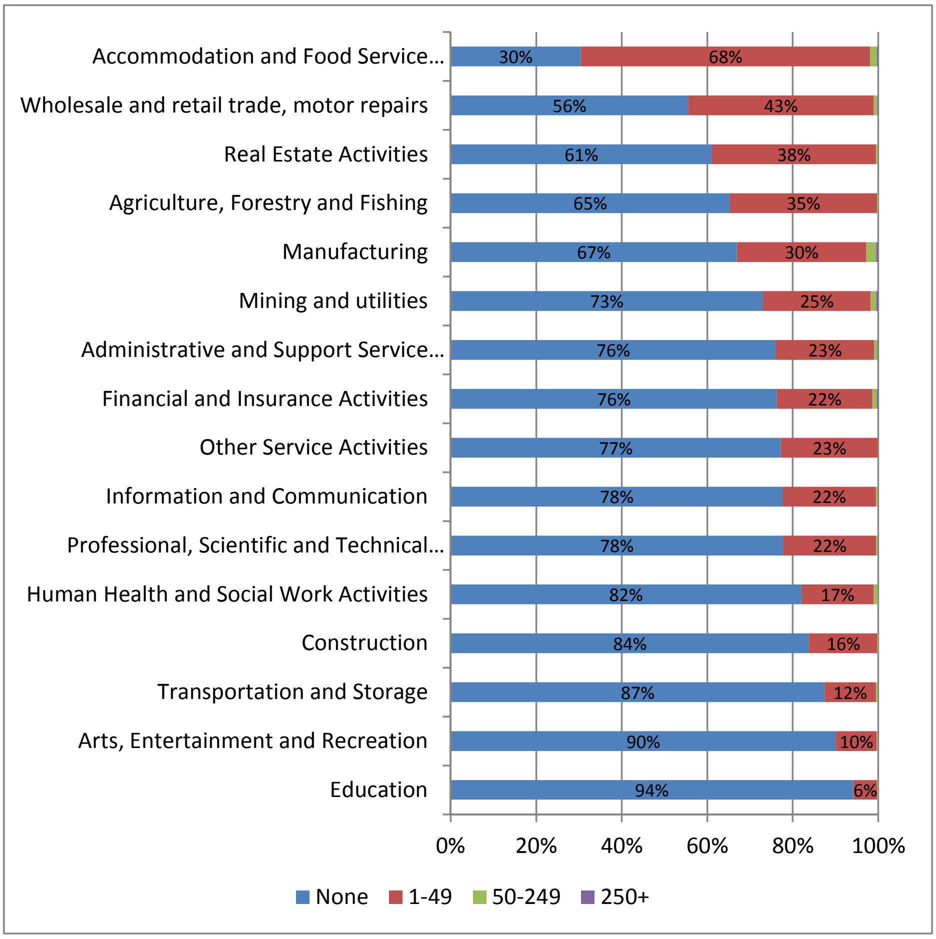
NOTES: HHI calculated for 4 digit sic codes within finance section. Employment data from NOMIS (BRES, 2015); data on SIC 6530, pension funds, was not available for 2015. Central banking activities are excluded (this sector is dominated by the Bank of England, a public sector institution in London).

Figure 4.B.2: Growth in number of firms, by size band (private sector only)



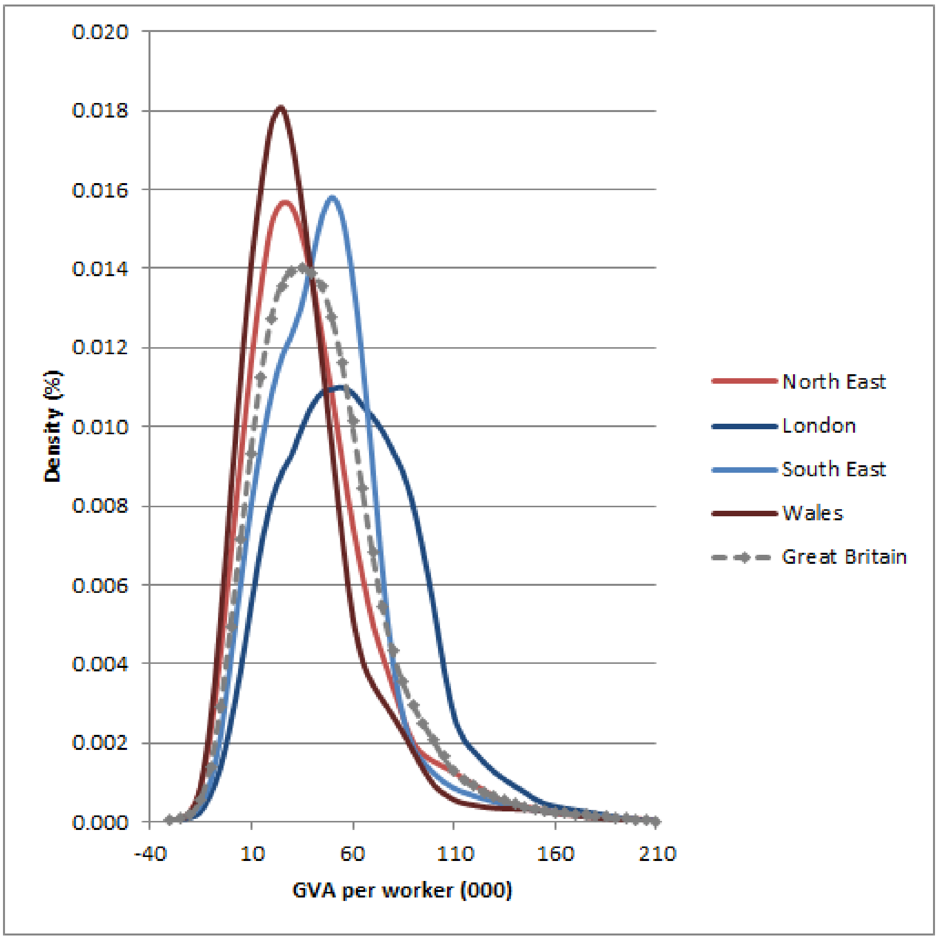
NOTES: BPE (2016) UK Time Series.

Figure 4.B.3: Private sector firms by size band



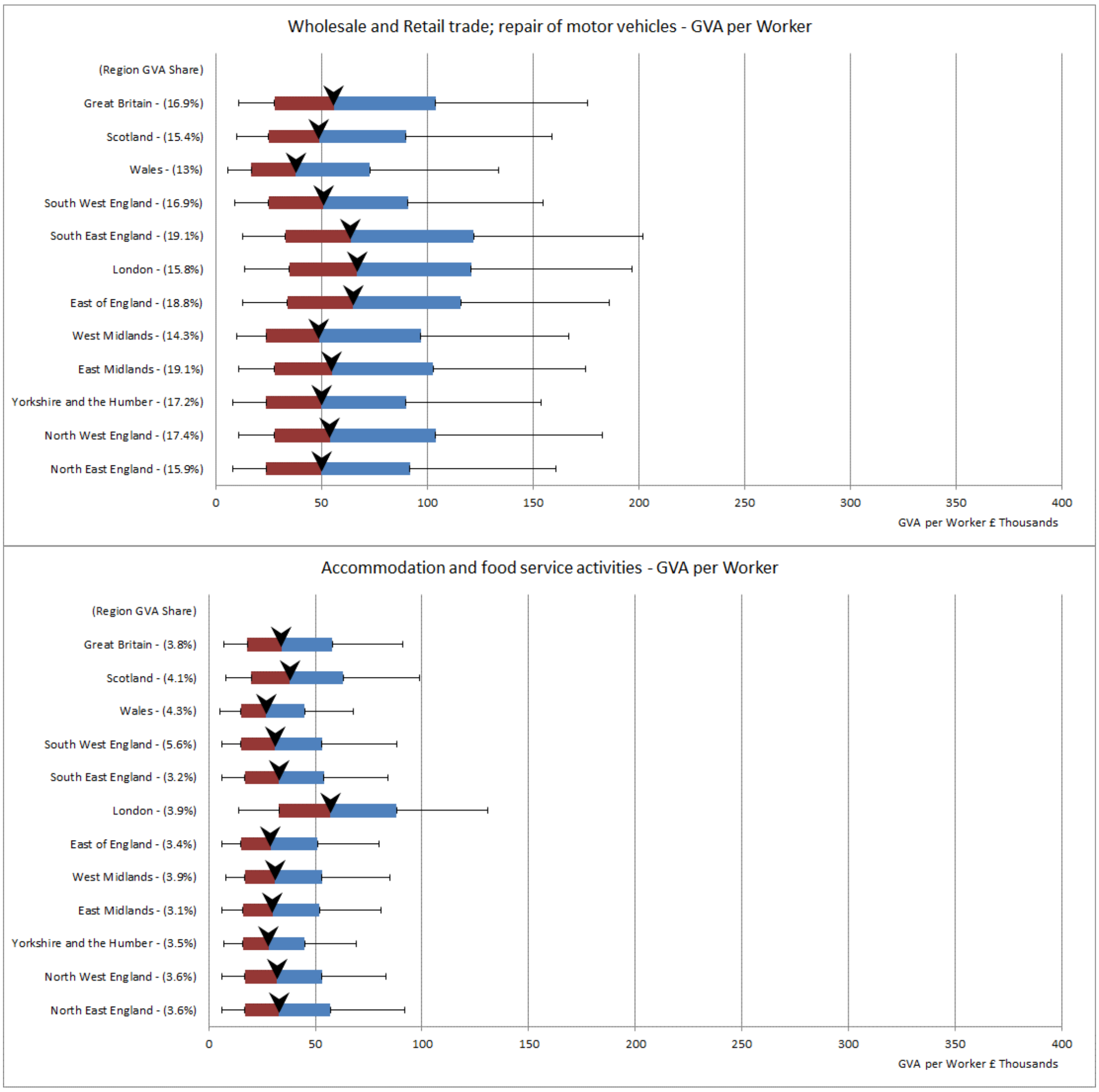
NOTES: BPE (2016) UK Industry Summary.

Figure 4.B.4: Distribution of GVA per worker in the non-financial business economy (2014)



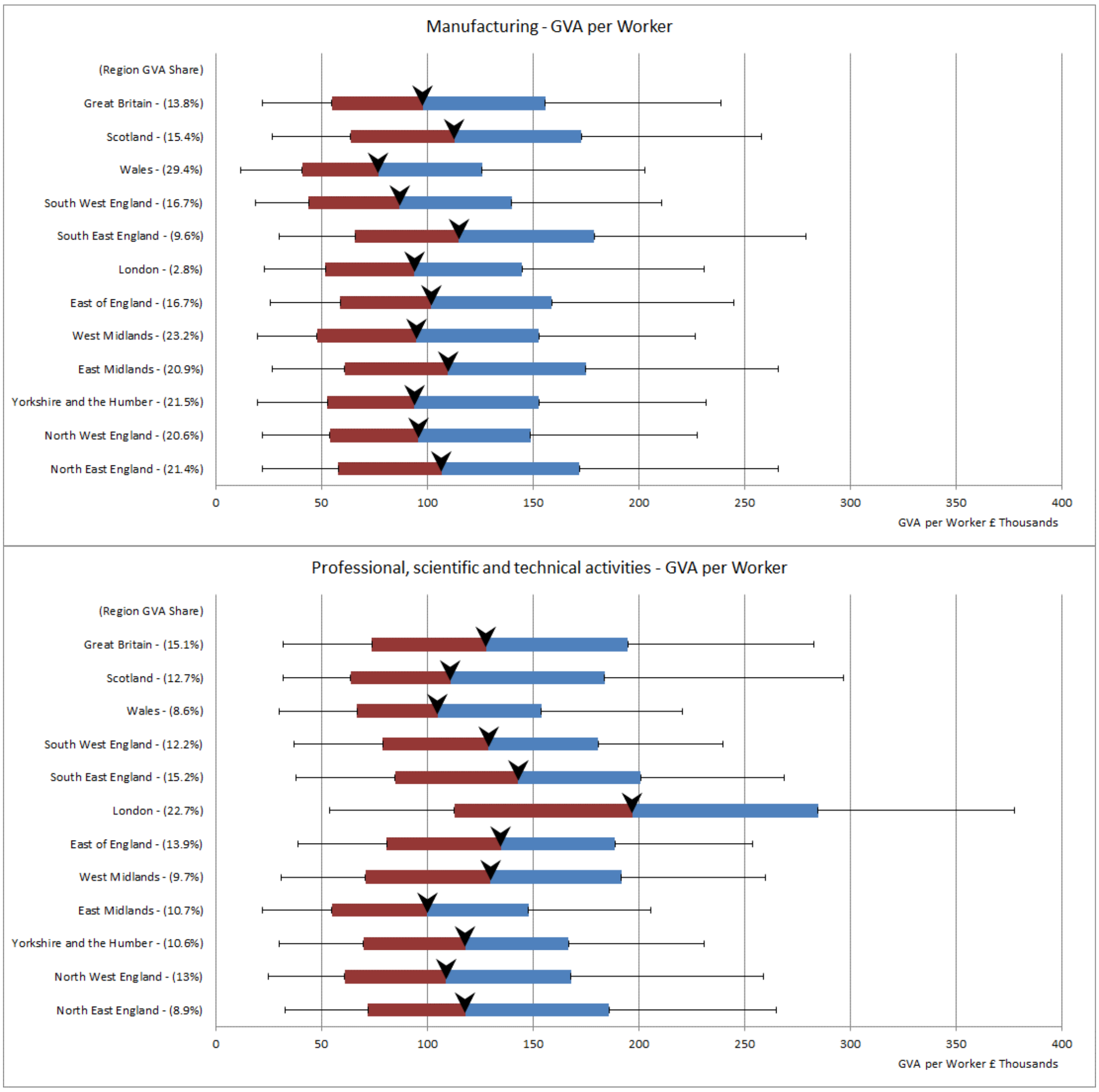
NOTES: ONS (2017) Regional firm level productivity analysis for the non-financial business economy Jan 2017. Analysis excludes Northern Ireland.

Figure 4.B.5: Distribution of GVA per worker in selected low productivity industries (2014)



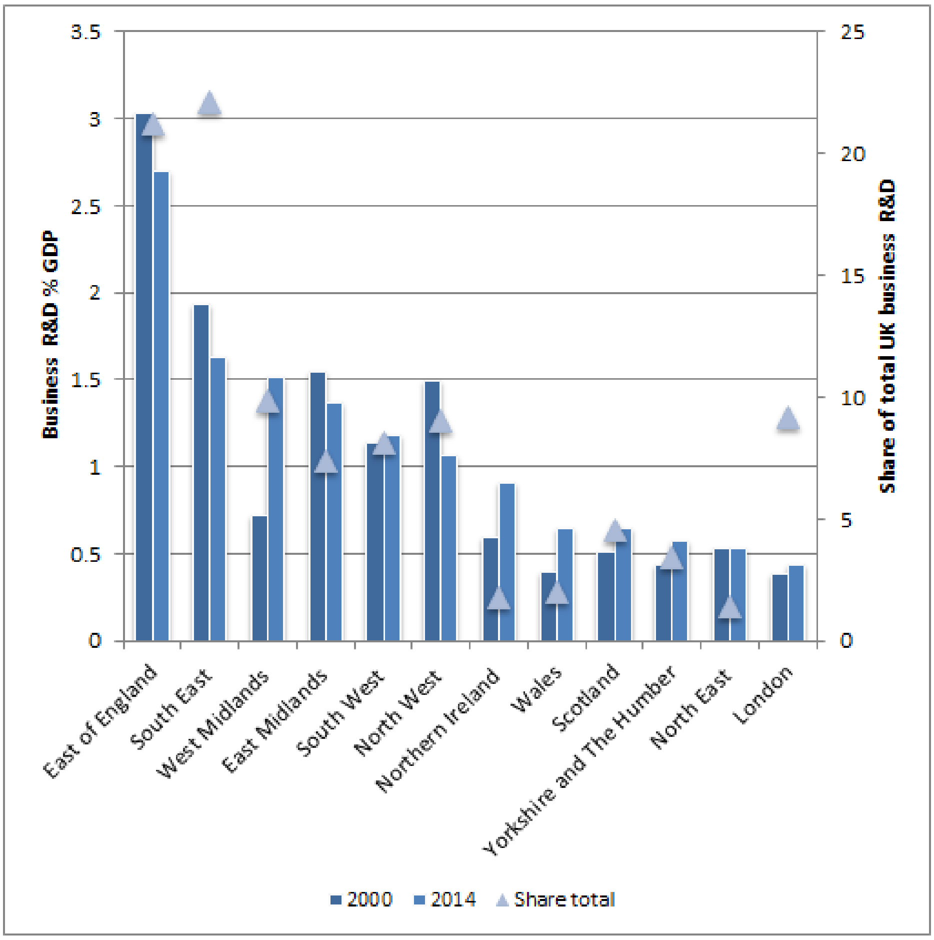
NOTES: ONS (2017) Regional firm level productivity analysis for the non-financial business economy Jan 2017. Analysis excludes Northern Ireland.

Figure 4.B.6: Distribution of GVA per worker in selected high productivity industries (2014)



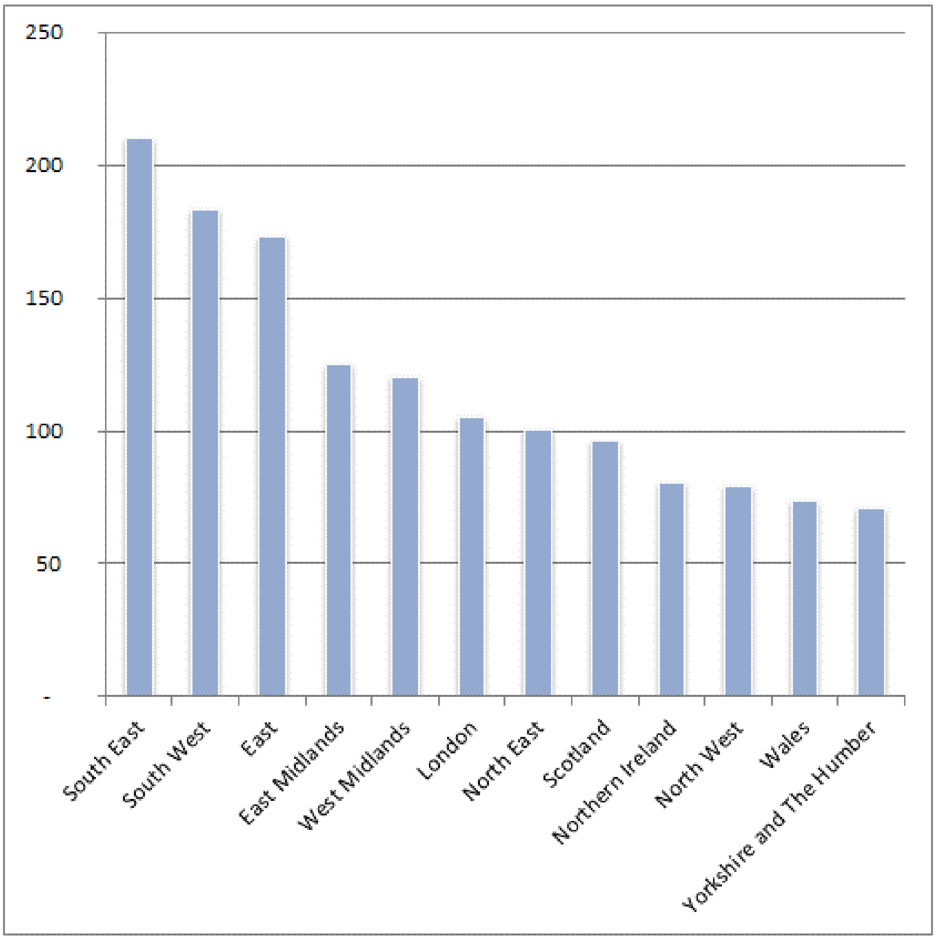
NOTES: ONS (2017) Regional firm level productivity analysis for the non-financial business economy Jan 2017. Analysis excludes Northern Ireland.

Figure 4.B.7: Business R&D as per cent of GDP and share of total UK



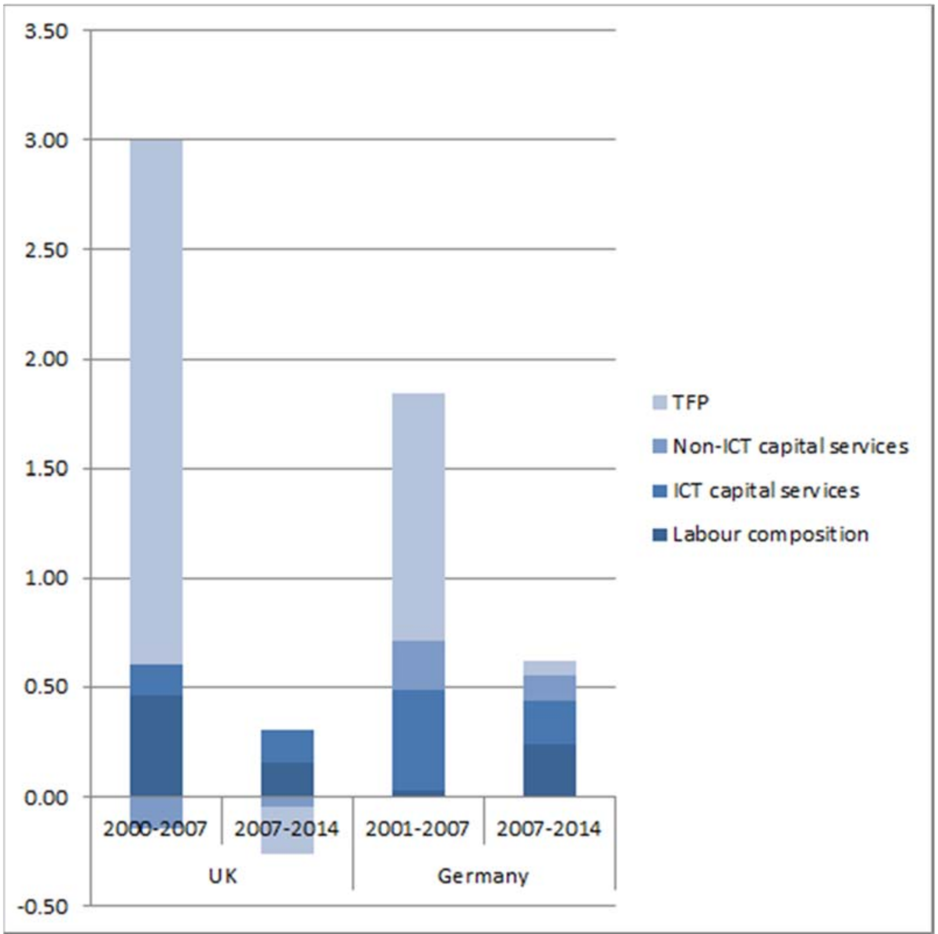
NOTES: Source: Eurostat, R&D expenditure by business. Last updated 3 Feb 2017.

Figure 4.B.8: Patents as a percentage of the active population



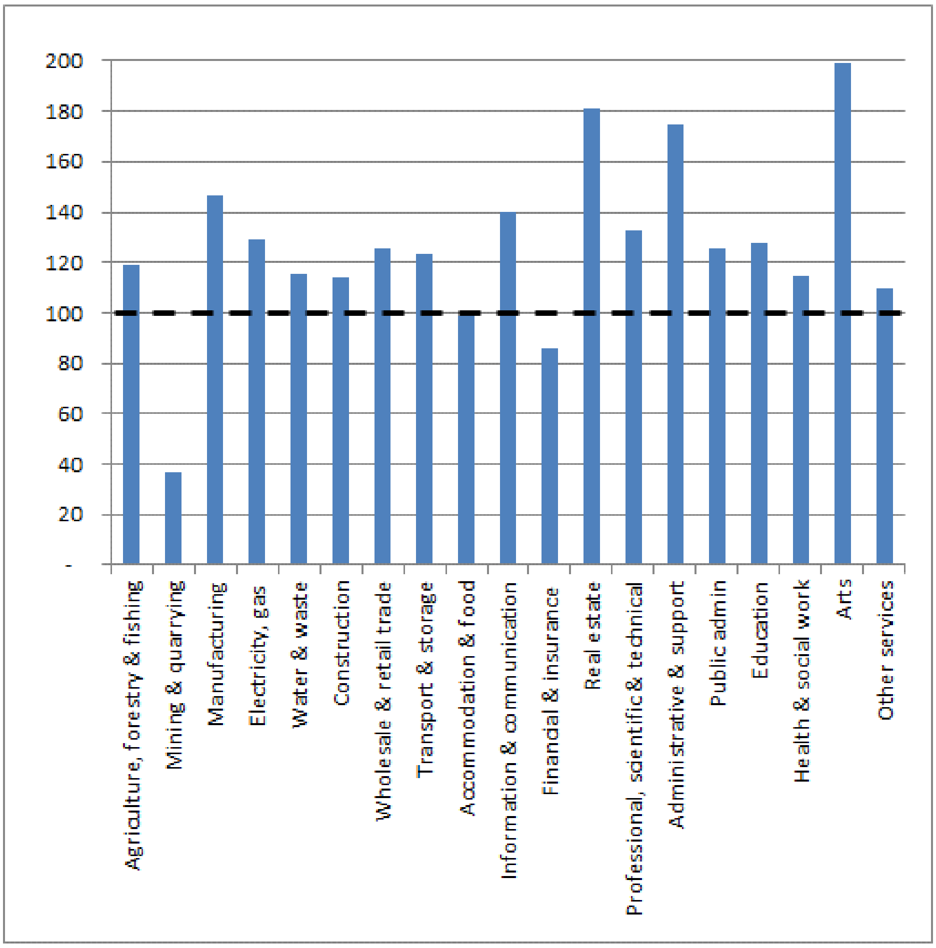
NOTES: Eurostat, Patent applications to the EPO by priority year by NUTS 1 regions.

Figure 4.B.9: Decomposition of GVA per hour growth by factor input



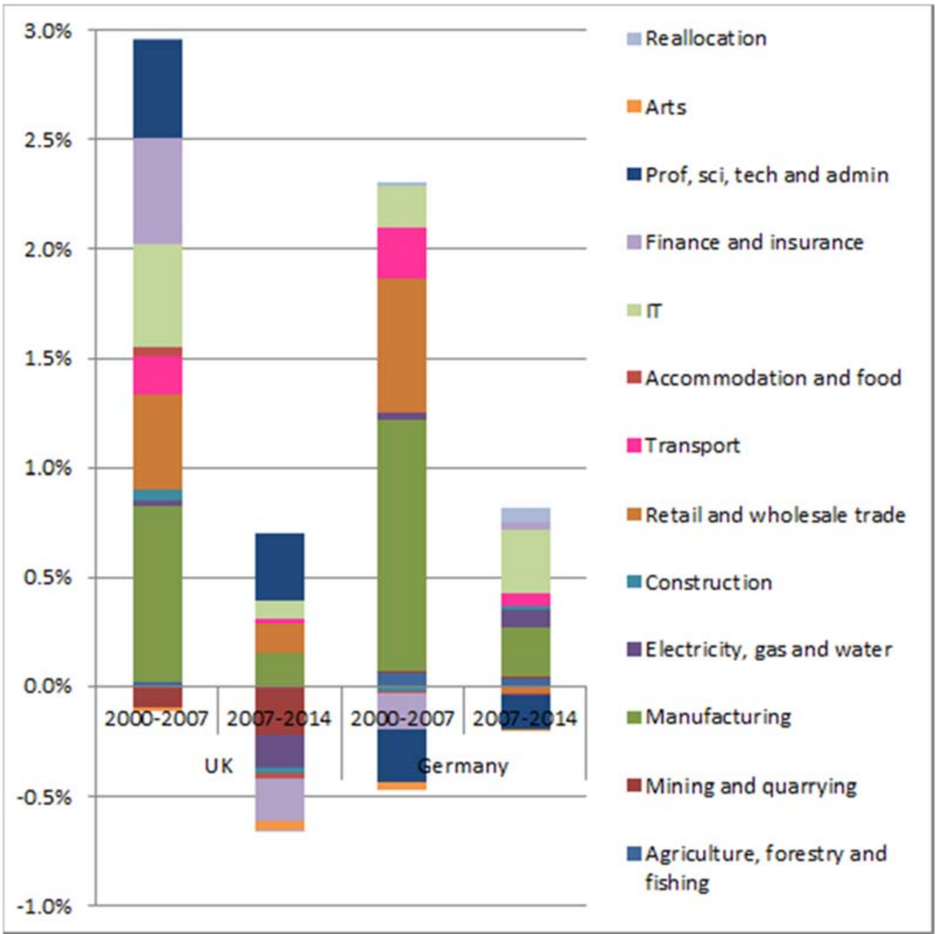
NOTES: Source: EU KLEMS

Figure 4.B.10: GVA per hour, by sector Germany versus UK (100), 2015



NOTES: Source: OECD STAN

Figure 4.B.11: Decomposition of GVA per hour growth by sector EU KLEMS



NOTES: Source: EU KLEMS

4.C Appendix Tables

Table 4.C.1: Industrial concentration, HHI (employment)

Sector	HHI
Mining & quarrying	0.209
Financial and insurance activities	0.038
Creative*	0.019
Electricity & gas, water & waste	0.015
Professional, scientific and technical activities	0.011
ICT	0.012
Agriculture	0.009
Real estate	0.009
Transport & storage	0.006
Public administration & defence	0.007
Admin & support services	0.007
Other service activities	0.006
Accommodation & food	0.006
Science and technology*	0.005
Arts, entertainment & recreation	0.006
Education	0.005
Utilities	0.005
Health & social work	0.005
Manufacturing	0.004
Retail, wholesale & motor	0.004
Construction	0.004

NOTES: Industry definitions: using standard SIC07 sections; *additionally high tech and creative industries as defined by NESTA (2015). Employment data from NOMIS (BRES, 2015).

Table 4.C.2: Car manufacturing plants, employment and local authority employment shares

Company	Local authority	Plant employees	share of emp	share manu emp
Nissan	Sunderland City Council	7,458	6%	36%
Jaguar Land Rover (Halewood plant)	Knowsley Borough Council	5,000	8%	42%
Mini (Cowley plant)	Oxford City Council	4,000	3%	89%
Bentley Motors	Cheshire East Council	3,830	2%	19%
Jaguar Land Rover (Solihull plant)	Coventry City Council	3,200	2%	18%
Honda	Swindon Borough Council	3,022	3%	30%
Toyota	South Derbyshire District Council	2,953	10%	42%
Vauxhall (Luton plant)	Luton Borough Council	2,500	3%	32%
Ford (Bridgend plant)	Bridgend Council	2,130	4%	27%
Vauxhall (Port Ellesmere plant)	Cheshire West and Chester Council	2,100	1%	16%
Ford (Dagenham plant)	Barking and Dagenham Borough	1,830	4%	37%
Aston Martin	Stratford-on-Avon District Council	1,495	2%	14%
Mclaren Automotive	Woking Borough Council	1,492	3%	37%
Rolls Royce	Rushmoor Borough Council	1,229	3%	35%
Lotus	South Norfolk District Council	1,025	2%	26%
BMW	North Warwickshire Borough Council	1,000	2%	17%
Mini (Swindon plant)	Swindon Borough Council	850	1%	9%
Morgan Motor	Malvern Hills Disctrict Council	137	1%	4%
Caterham Cars	Bexley Borough Council	114	0%	3%

NOTES: Car manufacturing plants obtained from SMMT, and employment data from Bureau Van Dijk. Local authority employment from NOMIS. 2 Rolls Royce plants are excluded as they focus on defence and civil engineering. Share of employment excludes private sector.