CMA Competition & Markets Authority

Industrial policies: New evidence for the UK

CMA Microeconomics Unit

9 April 2025
Report no. 3

Contents

1. Executive summary

1.1 The UK government has set out its vision for a modern industrial strategy in an Industrial Strategy Green Paper, published in November 2024. Details will be set out in the forthcoming Industrial Strategy White Paper, due in the first half of 2025.

1.2 The industrial strategy constitutes one pillar of the UK government's wider growth mission, alongside economic stability, investment, place, people, innovation and Net Zero.

1.3 In this report we analyse the industrial policies (that is, policies aimed at shaping the industrial composition of the economy) that may form part of a modern industrial strategy.

1.4 We undertake analysis to understand the UK's past industrial policy experience, the impact of past policies on productivity, investment, innovation, employment and competition, and the economic dynamism and competitive dynamics of the growth-driving sectors as identified in the UK government's industrial strategy green paper.[1]

1.5 The purpose of this analysis is to help the UK government achieve maximum impact as it finalises the design choices for its industrial strategy.

Anatomy of recent UK industrial policies, and international context

1.6 We show that in the last decade the use of industrial policies has increased around the world, with the UK in the middle of the pack.

1.7 Compared to peer economies, the UK has historically been more likely to use industrial policy tools in mining, trade, information and communication technologies, arts and entertainment, and the hospitality sector. This choice reflects the strategic priorities of past UK governments. There is some, but not complete, overlap with the eight growth-driving sectors of the new industrial strategy.

1.8 The UK has tended to favour tax credits (which as this report shows tend to be more effective on average than other tools) over "direct" financial

[1] The key sectors in the UK government's Industrial Strategy Green Paper are advanced manufacturing, clean energy, creative industries, defence, digital and technologies, financial services, life sciences and professional and business services.

measures, such as grants, guarantees, or loans. This contrasts with other OECD countries in our sample that rely more heavily on direct tools. The UK has also given out less in direct subsidies as a share of GDP than most other European countries.

1.9 The UK's focus on tax credits could reflect its comparatively service-driven economy; at the country level, there is a positive relationship between the relative size of the manufacturing sector, and the percentage of industrial policy spending in that country via direct instruments.

The impact of past industrial policies on productivity, employment, investment and competition

1.10 Industrial policies are designed to achieve certain outcomes: for example, to increase productivity, build geopolitical resilience, pivot towards greener technologies or support employment in economically distressed communities.

1.11 They are therefore almost by definition targeted at industries and businesses that in some important way stand out from the rest of the economy.

1.12 When we look at an outcome (for instance, productivity), we therefore need to distinguish between a *selection* effect (that is, productivity in targeted industries might be different from the outset) and a *treatment* effect (that is, industrial policies cause productivity to increase).

1.13 We show that on average, industrial policies have tended to target higher productivity industries. If we fail to account for this, we overestimate the effect of industrial policies on productivity. Of course, there may be good reasons to target industrial policies at higher-productivity sectors.

1.14 Once we account for selection as best we can with the data available, we find that on average industrial policies across the OECD in recent years followed by a small productivity increase in targeted sectors over a two-year horizon. Productivity effects may be larger in the long run, but we cannot test this with the data available. The small effect we find is also estimated across policies implemented with potentially many different goals in mind.

1.15 Based purely on the average of recent policies, a one percentage point increase in industrial policy spending as a share of GDP leads to about a 0.25% increase in labour productivity in the targeted industries. The proposed new industrial strategy presents an opportunity to improve on the effectiveness of these policies, by targeting productivity specifically.

1.16 Employment, investment or research and development (R&D) spending undertaken by targeted sectors do not rise differentially on average over the following two years in response to an increase in industrial policy spending, based on past policies.

1.17 Market power (as measured by firms' cost markups) and industry concentration do not seem to change in response to observed industrial policy changes. This suggests that industrial policy and competition policy are not necessarily in conflict.

1.18 In areas of this report, we comment on the overall effects of past industrial policies. We have done so on the basis that understanding the average impact of even a wide set of policies can support specific design choices in the future.

1.19 We have also sought to look beyond the average impacts of industrial policies as a whole and examine how effects vary by industrial policy type.

1.20 For instance, the introduction of a tax credit policy is associated with a productivity effect approximately ten times that of other measures. Meanwhile, many other policies have negligible or no effects on labour productivity.

1.21 This demonstrates the importance of considering specific design choices as the industrial strategy is developed and implemented. All our results should of course be treated with caution given the challenges of isolating the policy treatment effect from selection.

Impacts of industrial policies by UK region and nation

1.22 Another way of estimating the impact of industrial policies is to look at the regional exposure to national industrial policy changes, due to a region's pre-existing industry mix. This approach has the advantage of being potentially less subject to industry selection effects.

1.23 Using this approach, we likewise find that industrial policies increase productivity by a small and marginally statistically significant amount. The introduction of one additional industrial policy measure on average raises productivity by 0.5% over the following two years.

1.24 Unlike at the national industry level, we find a modest positive effect of industrial policies on local employment. Workers moving from one region to another in response to a policy change may account for this difference.

1.25 When looking at subsidies specifically, as a percentage of regional GDP, Wales and the Yorkshire and Humber region have received proportionately larger shares of UK subsidy spending.

1.26 Across the regions and devolved nations, firms of different sizes have received subsidies. In general, large firms account for a disproportionate share of subsidies.

1.27 However, industrial policies in London tend to favour mid-sized firms, and in Yorkshire and the East of England, the largest share of subsidies goes to micro-firms. These differences may have implications for the efficiency of subsidies, and for the resulting market structure in relevant industries.

New evidence on UK's growth-driving sectors

1.28 We also provide new evidence on the UK's growth-driving sectors, as defined in the Industrial Strategy Green Paper. We find that the growth-driving sectors are generally more productive, more dynamic and more competitive than the whole-economy average.[2] Investment rates however are generally low, both compared to the rest of the economy and to their equivalents in peer countries.

1.29 There is substantial variation within each of the eight growth-driving sectors. Some component industries (such as battery manufacturing within the clean energy sector) are much more concentrated, much less dynamic, and invest less than others.

1.30 This suggests careful attention to sector dynamics will be crucial for the success of the UK government's industrial strategy. In the more concentrated target industries, the UK government may for instance consider additional interventions aimed at increasing dynamism and competition.

1.31 By analysing UK supply chains, we find that the key growth sectors display high centrality, which means they are directly and indirectly connected to many other industries in the economy, and high upstreamness, which means that they supply many other industries. Together, these attributes indicate that

[2] For this part of the analysis, we omit finance and defence due to well-known measurement issues of inputs and outputs.

the chosen target sectors are well-placed to deliver wider indirect productivity and employment impacts.

1.32 The geographic distribution of growth-driving sector establishments differs from the distribution of past industrial policies and subsidies. The impacts of the industrial strategy may therefore vary across regions and devolved nations.

Industrial policies in the context of the wider growth mission

1.33 We also review the UK's performance on measures relating to the other pillars of the growth mission. Joint analysis of sector-specific (or "vertical") and economy-wide (or "horizontal") policies ensures that the different components of the growth mission work towards the same goal.

1.34 Our analysis pinpoints growth pillars where the UK fares worse than international peers, such as investment and innovation, but also suggests some bright spots, particularly in services trade and the transition to Net Zero.

1.35 Our analysis of sector-specific growth pillar outcomes suggests that investment and skills may represent bottlenecks for specific growth-driving sectors that limit the effectiveness of vertical industrial policies. For instance, skill shortages are particularly acute in the life sciences.

1.36 These interdependencies between industrial policies and other pillars of the growth mission imply that vertical policies are likely most effective when designed alongside wider horizontal policies on, for instance, investment, skills, and innovation.

Open questions and further work from the Microeconomics Unit

1.37 We highlight four data and evidence gaps that it would be helpful to fill to ensure effective monitoring and evaluation of the government's new industrial strategy.

1.38 First, accurate sector definitions are crucial for understanding the industry and regional impacts of an industrial strategy. Standard Industrial Classification (SIC) codes, while useful for international comparability, are particularly problematic for emerging sectors of the economy (such as many of the growth-driving sectors).

1.39 This points to a need for better understanding of regional industry clusters, particularly for start-ups and emerging technologies. The Microeconomics Unit plans to undertake work to help address this evidence gap later this year.

1.40 Second, any industrial strategy will benefit from better evidence on the other pillars of the growth mission. There are two reasons for this: first, the UK's relative strengths and weaknesses determine how much of a focus the industrial strategy should be overall, compared to other policies. A comprehensive view ensures a coherent strategy and value for money overall. Second, a sector-specific analysis of growth pillars allows policymakers to identify sector-specific constraints. For instance, where sector-specific skills shortages are acute, industrial policies are less likely to have an effect. This ensures industrial policies can be maximally effective.

1.41 In addition to the evidence in this report, the CMA Microeconomics Unit has announced two further research projects to understand complementary growth pillars. We are reviewing the literature on investment over the business lifecycle, and how competition shapes investment opportunities. We are also bringing together new evidence on technology diffusion across the UK economy, and the role of competition in this process. We expect to publish findings from both projects in the coming months.

1.42 Third, this report highlights that knowledge of supply chains at a much more granular level is crucial for understanding both potential bottlenecks and spillover effects. Where key input providers cannot expand or are not resilient, industrial policies aimed at growing an industry's productivity or turnover will be ineffective. The location of upstream and downstream industries also matters for understanding the geographic impacts of industrial policies.

1.43 In follow-up work, we are studying the changing nature of supply chains in more detail and provide evidence on how cost and productivity changes propagate through them. This analysis will allow policymakers to understand the wider impact of industrial policies across the whole economy, and to consider other policy goals, such as resilience.

1.44 Finally, the selection effects inherent in industrial policy make it difficult to evaluate the causal impact on outcomes of interest, such as productivity, employment, or investment.

1.45 Policymakers may therefore want to consider building data gathering and design features into industrial policies that make it easier to measure the success of chosen policies and adjust them if they fail to meet stated goals.

1.46 Clear published guidance about the growth-driving sector definitions, processes to track the implementation of policies and broad access to implementation data would enable government analysts and the wider research community to build evidence that the UK government can use to refine and adjust its industrial strategy.

1.47 Other parts of the CMA also contribute to the evidence base to inform the UK government's industrial strategy. In 2026, the CMA's Subsidy Advice Unit will publish a report on the effectiveness of the UK's subsidy control regime and its impact on competition and investment. The Microeconomics Unit's research on industrial policy is separate to the Subsidy Advice Unit's monitoring work but may inform it.

2. What instruments are countries using, and when?

2.1 Industrial policies are policy tools governments can use to shape the industrial composition of their nation's economy. When combined to achieve a particular goal, they form an industrial strategy.

2.2 In this report, due to data constraints, we focus on financial instruments targeted at specific firms: for instance, tax credits, favourable loans, or direct capital injections. Researchers call these tools "vertical" (because they affect specific sectors or groups of firms).

2.3 But governments also have a wide toolbox of less direct tools: they can set technical standards, shape competition policy, and legislate data use policies. Because these tools apply across the whole economy, they are often called "horizontal".

2.4 Not all countries use industrial policies to the same degree. And even where the level of spending on industrial policies may be similar, different countries tend to prefer different tools.

2.5 We show that in recent years the UK has been neither a leader nor a laggard in the pursuit of industrial policies, regardless of whether we look at the number of new policies adopted, or spending levels.

2.6 Compared with peer nations, the UK is more likely to favour indirect government spending for industrial policy (such as tax credits) over direct spending (such as capital injections). This preference is common among economies that lean more heavily towards services than manufacturing. In line with its preference for indirect tools, the UK spends a smaller share of GDP on direct subsidies, compared to its European peers.

2.7 In terms of industries, the UK in recent years has outspent peer OECD nations in mining (which includes oil and gas extraction, a very capital-intensive industry), wholesale and retail trade, information and communication technology, arts and entertainment, and hospitality. This likely reflected the strategic priorities of the government at the time.

2.8 There is some, although imperfect, overlap with the UK government's announced growth-driving sectors. This suggests some continuity and some change from the past.

Defining industrial policies

2.9 There is no commonly agreed definition of the terms “industrial policy” and “industrial strategy”, but researchers and policymakers often find it useful to classify tools along certain dimensions.

2.10 First, we can distinguish between vertical tools (those used on specific firms, or within a given industry or industries only) and horizontal tools (those applied across the economy).

2.11 Second, we can distinguish between direct tools (those that involve governments disbursing money to firms) and indirect tools (those that create incentives through the tax system).

2.12 Third, we can distinguish between supply-side tools (those that focus on changing inputs, technologies or firms directly), demand-side tools (those that seek to influence an economy by encouraging demand for certain goods and services) and wider governance tools (those that seek to influence the rules of the game).

2.13 Finally, some researchers draw a line between within-firm tools (those that create incentives for firms to change their inputs and ways of working) and between-firm tools (those that aim to shift production from less productive to more productive firms).

2.14 The IMF in its country surveillance documents defines industrial policy narrowly as vertical policies aimed at supporting specific firms, industries or economic activities.

2.15 In contrast, an influential OECD working paper by Criscuolo, Gonne, Kitazawa and Lalanne (from which the categorisation above comes) takes a much broader view, encompassing within-firm and between-firm supply instruments, demand instruments and governance instruments in its definition. Warwick summarises views along the whole spectrum from narrow to broad.

2.16 We follow the framework implicit in the UK government’s announcements on its industrial strategy and the wider growth mission. In these terms, the growth mission is the collective set of policies, both horizontal and vertical, designed to achieve the stated economic and industrial goals (first and foremost, sustained economic growth).

2.17 In this framework, and therefore our report, an industrial strategy is predominantly defined as a set of vertical, sector-focused policies. This means that our definition is closer to the IMF’s definition of industrial policy than the OECD’s (which in the UK context better describes the overall growth mission).

Measuring industrial policies

2.18 Accurately measuring the extent of industrial policies is difficult, for two reasons. First, industrial policies are by definition policies enacted with the intent to shift or maintain the industrial composition of an economy. This means that identifying them requires assigning an intent. This is not straightforward.

2.19 Even policies that appear horizontal on paper may have a vertical, industrial-policy intent. For instance, skills policies or infrastructure construction may be regionally focused to alleviate a particular industry bottleneck. But inferring these vertical components of notionally horizontal policies is difficult.

2.20 Second, in many Western economies, explicit industrial strategies have largely fallen out of favour since the 1980s, only becoming popular again recently. As a result, most datasets on industrial policy are of recent vintage. This limits both the time periods covered, and the geographic and industry coverage available.

2.21 We use three datasets to measure and understand industrial policies. Juhász, Lane, Oehlsen and Pérez have developed a text-based classification of an existing database of policies, the Global Trade Alert database (GTA).

2.22 The GTA contains what its creators define as credible announcements of meaningful and unilateral changes in the relative treatment of foreign versus domestic commercial interests in an industry or set of industries, from 2008 onwards.

2.23 Not all GTA entries are industrial policies. Therefore, Juhász, Lane, Oehlsen and Pérez train a machine-learning algorithm on this text-based dataset to identify policies that explicitly aim to shape the composition of economic activity.

2.24 This filtered version of the GTA covers many countries, at an equivalent of the three-digit Standard Industrial Classification (SIC) level. However, given the input data source, we only have counts of policies classified as industrial policies, and the type of instrument they constitute. This dataset cannot tell us how much money governments spend on each measure.

2.25 We therefore complement this data with the OECD’s Quantifying Industrial Strategies (QuIS) dataset. QuIS is a recent effort by the OECD to collect much more detailed information on industrial policies in member countries, including expenditures. This level of detail however comes at a cost, in terms of smaller geographical coverage, broader industry detail (available only at the section level) and shorter time span.

2.26 QuIS defines industrial policy expenditures as “direct support extended by the public sector to businesses, aimed at promoting investment (including digitalisation and cleaner production), improving competitiveness, or supporting economic development”.

2.27 QuIS classifies industrial policy expenditures into five categories: grants, loans and loan guarantees, tax expenditures (allowances, exemptions, rate relief and credits) and venture capital investments. We consider grants and venture capital investments as direct instruments, and include loans, loan guarantees and tax expenditures in our definition of indirect instruments.

2.28 Finally, for direct subsidies, we clean and combine the EU State Aid database covering 2016-2023 and the UK subsidies database covering 2021-2023.

2.29 When discussing subsidies, and comparing them to other industrial policy tools, we follow how these terms are generally used in economic research. Others may adopt broader or narrower definitions (see for instance the Department for Business and Trade’s statutory guidance on subsidy control).

2.30 Evenett, Jakubik, Martin and Ruta have built yet another new dataset on industrial policies. They identify some non-economic rationales for industrial policies, including tit-for-tat behaviour. Since this dataset only begins in 2023, we do not use it in this report.

Industrial policies have increased across the world

2.31 The popularity of industrial policies has ebbed and flowed over time. Juhász and Steinwender for instance describe the wide range of policies governments have employed over the course of the 19th century to guide their economies towards industrialisation. These include interventions in input markets, skills policies, and outright acquisition of technologies.

2.32 More recently, methodological and data advances have revealed new insights on some of the 20th century’s most well-known examples of industrial policy.

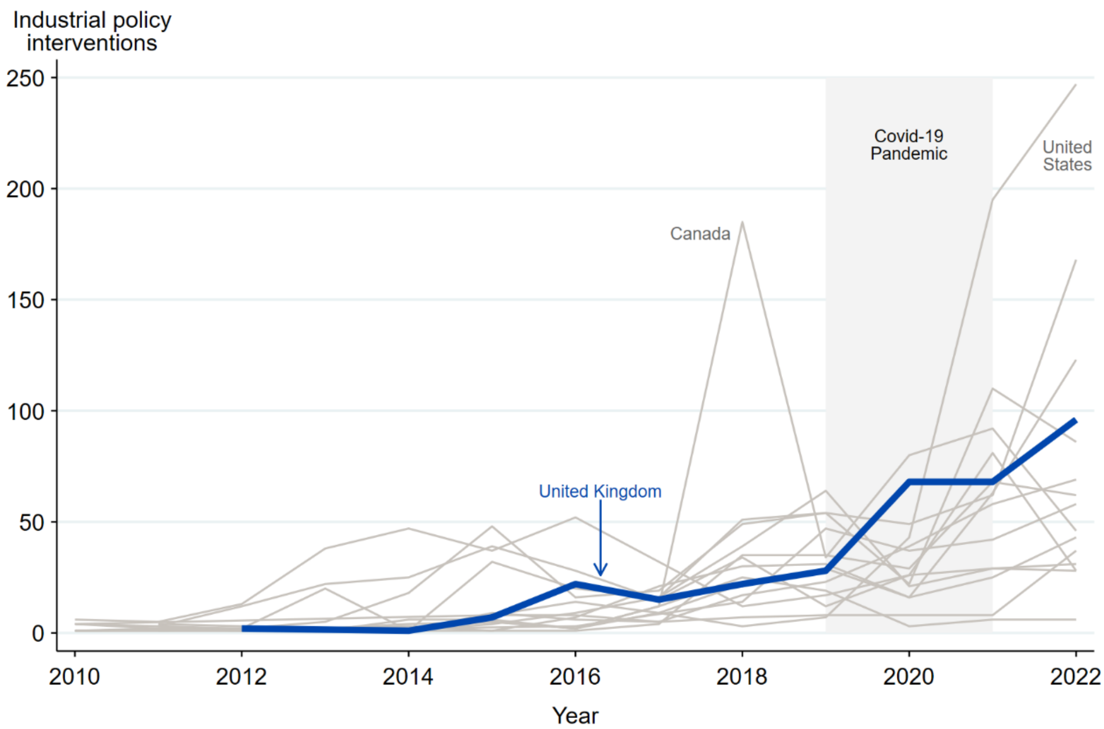
2.33 For instance, Lane evaluates South Korea’s heavy and chemical industry drive in the 1970s and finds persistent effects in both targeted industries and those further downstream. Choi and Levchenko quantify these effects as amounting to a 3-4% increase in aggregate welfare, predominantly through productivity benefits from learning-by-doing.

2.34 In recent years, industrial policy has again been in the ascendant. Figure 2.1 plots the number of new industrial policy interventions by year, for the UK and comparable countries, between 2010 and 2022, using the measure developed by Juhász, Lane, Oehlsen and Pérez.

2.35 Two facts stand out. First, industrial policies have increased in popularity in most advanced economies since 2016. Second, the UK, with about one hundred new interventions by 2022, is neither a leader nor a laggard internationally. The UK's relative position among its peers is robust to other ways to treat the data, as shown in Figure E.1 in the appendix.

Figure 2.1: The use of industrial policies has increased around the world

New industrial policies, for fifteen countries, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database



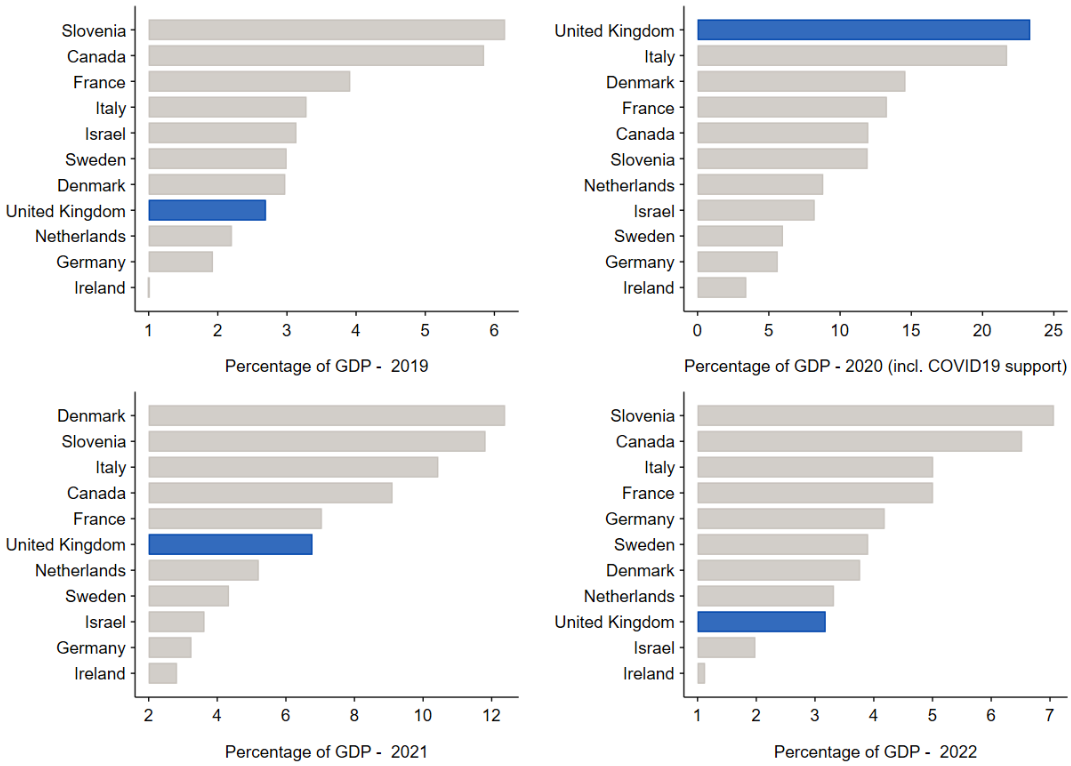
Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. The plot only considers policies published the same year they were announced and includes the 15 countries with the highest number of IP in the period 2010-2022. The other countries included are Argentina, Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Russia, South Korea, Spain, and US. Source: *Global Trade Alert* (2010-2022)

2.36 Figure 2.2 shows a similar picture in spending levels, using data from the OECD's QuIS database. The UK spends roughly around 3% of GDP on industrial policies, except during the Covid-19 pandemic, when pandemic-related business support programmes more than doubled this amount.

2.37 Recent research has sought to characterise and understand the use of industrial policies. Juhász, Lane, Oehlsen and Pérez argue that industrial policies are not only common, especially in richer countries, but that countries use a sophisticated mix of instruments to target specific recipients, often in industries with revealed comparative advantage.

Figure 2.2: Except for 2020, the UK spends less than many OECD peers

Annual industrial policy expenditures, 2019-2022, from the OECD Quantifying Industrial Strategies database



Yearly expenditure on industrial policy as a percentage of GDP in each country over the period 2019-2022. Countries are ranked by total expenditure as a percentage of GDP. Data from *Quantifying Industrial Strategies (QuIS)* (2019-2022).

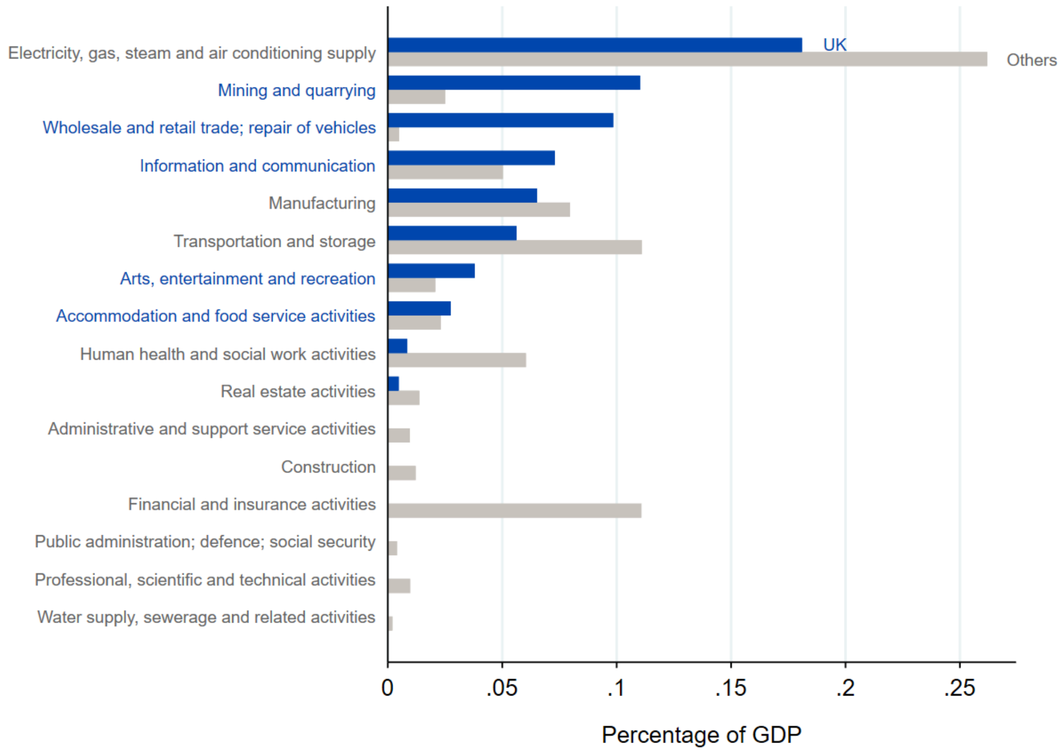
2.38 Bown examines industrial policy through the lens of the existing global trading system, embodied by the World Trade Organisation (WTO). He argues that four factors have led to the recent rise of industrial policy: the rise of China and its integration into global value chains; the desire for national supply chain resilience in the face of shocks; supply chain responsiveness, or the ability to use supply chains to react to events; and an increased willingness to reorient domestic economies towards Net Zero.

2.39 Figure 2.3 plots the total amount of spending by sector over the period 2019-2022, using data from the OECD's QuIS project. Compared to the other ten OECD countries included in this dataset, the UK spends comparatively more on industrial policies covering mining and quarrying (likely driven by investment tax credits for oil and gas extraction, a very capital-intensive industry), wholesale and retail, information and communication, arts and entertainment and accommodation and food services.

2.40 In absolute terms, the UK also spends substantial amounts on utilities (the largest recipient sector), manufacturing and transportation and storage.

Figure 2.3: Comparatively, the UK has favoured mining, trade, and the arts

Sectoral industrial policy spending as a percentage of GDP, UK and OECD peers, 2019-2022, from the OECD Quantifying Industrial Strategies database



Average expenditure by the UK and other OECD countries on each economic activity as a percentage of GDP in the period 2019-2022. Other includes: Canada, Denmark, France, Germany, Ireland, Israel, Italy, Netherlands, Slovenia, and Sweden. Activities are ranked by the total percentage expenditure by the UK in the period 2019-2022. Observations for which there is no specified economic activity are omitted. Data from the OECD *Quantifying Industrial Strategies (QuIS)* (2019-2022).

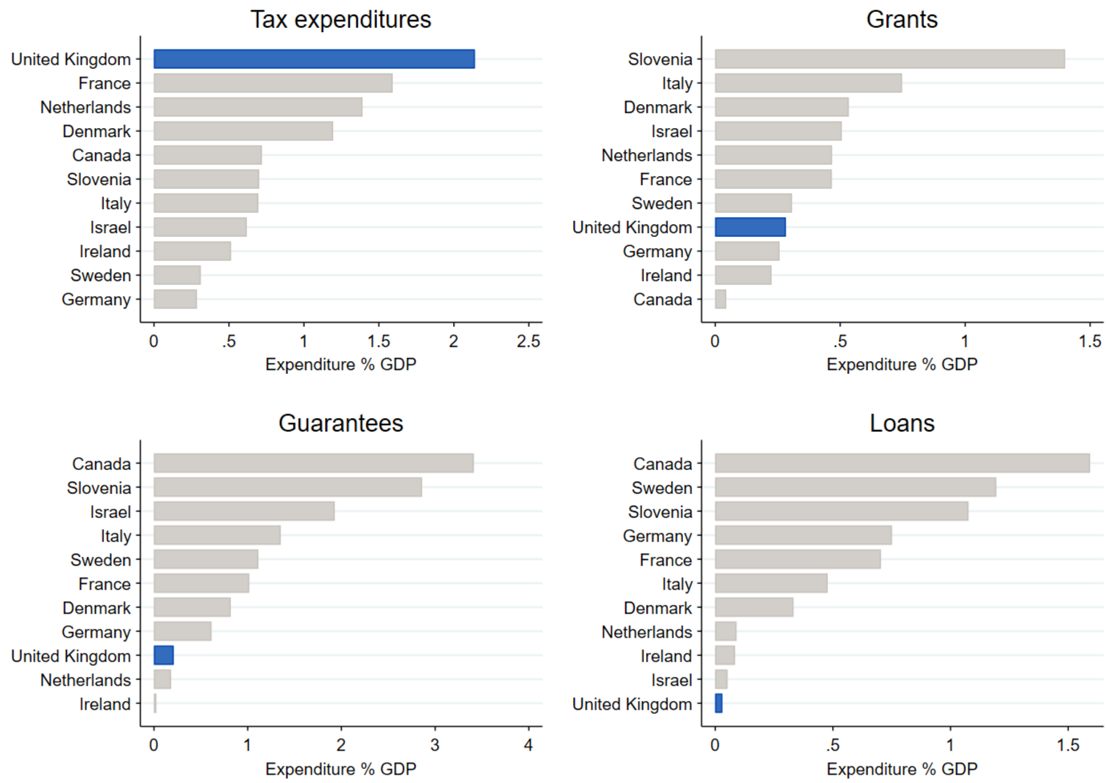
The UK uses more tax credits than peer countries

2.41 The UK not only differs from other countries in the number of industrial policies and the sectors covered, but also in the type of instruments used. Figure 2.4 shows the share of GDP across four types of industrial policies: tax expenditures (or tax credits for short), grants, guarantees, and loans.

2.42 The UK spends over two percent of GDP on tax credits, significantly more than any other country in the dataset. By contrast, the UK is at or near the bottom of the distribution when it comes to expenditure on grants, guarantees or loans.

Figure 2.4: The UK predominantly uses tax credits

Industrial policy spending across types of instruments, UK and OECD peers, 2019, from the OECD Quantifying Industrial Strategies database

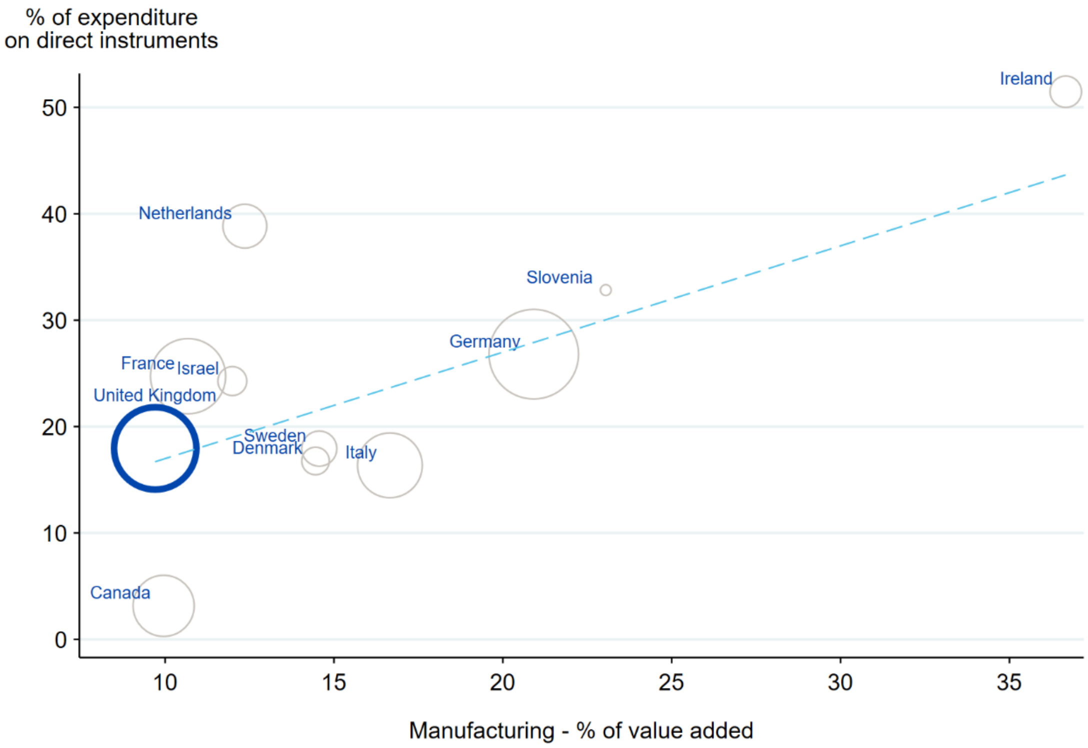


Share of GDP spent by each country on different industrial policy tools in 2019. Source: *Quantifying Industrial Strategies* 2019-2022.

2.43 This pattern is not unique to the UK. Figure 2.5 shows that countries with a relatively smaller manufacturing sector (such as Canada or the UK) generally spend less on direct industrial policies (such as grants or capital injections), and more on indirect industrial policies (such as tax credits, guarantees and loans).

Figure 2.5: Manufacturing-heavy countries are more likely to use direct instruments

Expenditure on direct tools and the manufacturing share, UK and OECD peers, 2019-2022, from the OECD Quantifying Industrial Strategies database



Direct instruments consist of grants and venture capital. Indirect instruments consist of guarantees, loans and tax expenditures. The percentage of expenditure is computed in the period 2019-2022. Each marker size reflects the relative size of countries' average GDP (USD, constant prices) for 2019-2022. Sources: *OECD* (2019-2022), *Quantifying Industrial Strategies* (2019-2022), and *World Bank* (2019-2022).

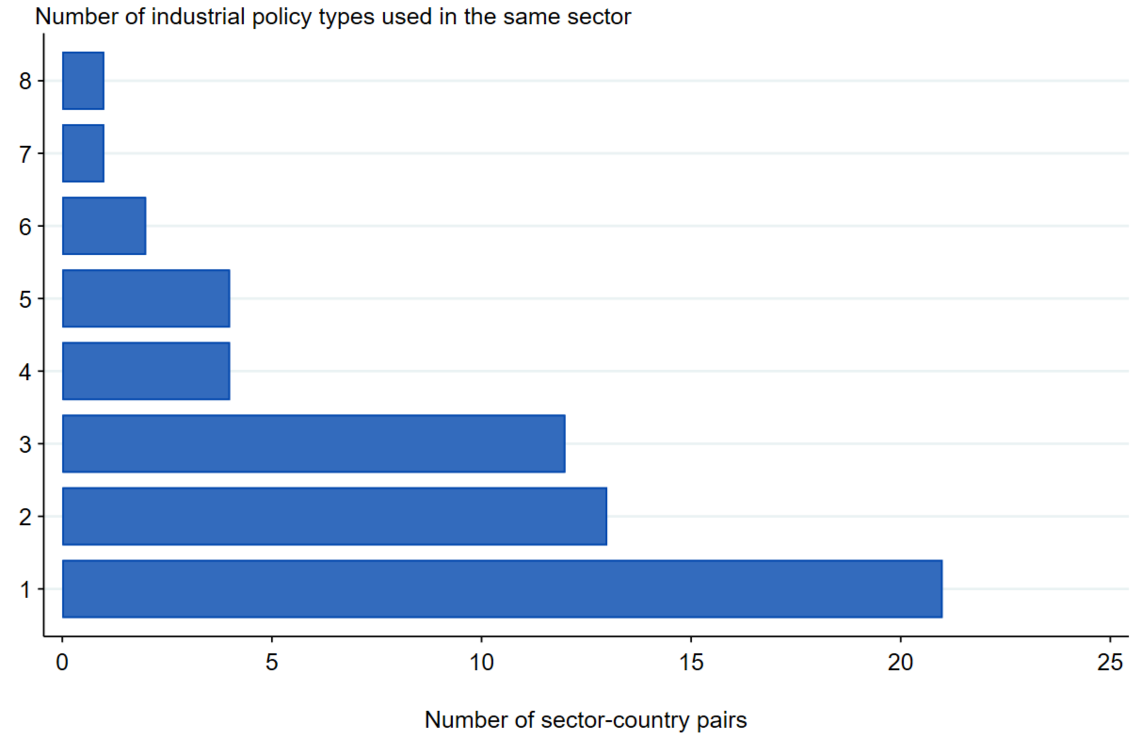
2.44 Figure 2.6 shows the number of active industrial policies in country-sector pairs in the QuIS database. Most industries do not receive any industrial policy support, while a small number are targeted by six or more each.

2.45 Figure E.2 in the appendix formally groups industry-country pairs via hierarchical clustering. This exercise confirms that most country-sector pairs are not targeted by industrial policies at all, with the remainder receiving a wide range of different policy combinations.

2.46 Academic research has also started to investigate how policymakers have used the toolset at their disposal in individual industries. For example, Barwick, Goldberg, Kwon, Li and Zahur study subsidies in the global electric vehicle market and find that consumer subsidies and local content requirements are by far the most used tools. Direct subsidies to firms on the other hand are less common.

Figure 2.6: Across the OECD, a small number of industries are the target of many industrial policies

Number of industrial policy interventions per sector, 2019-2022, from the OECD Quantifying Industrial Strategies database



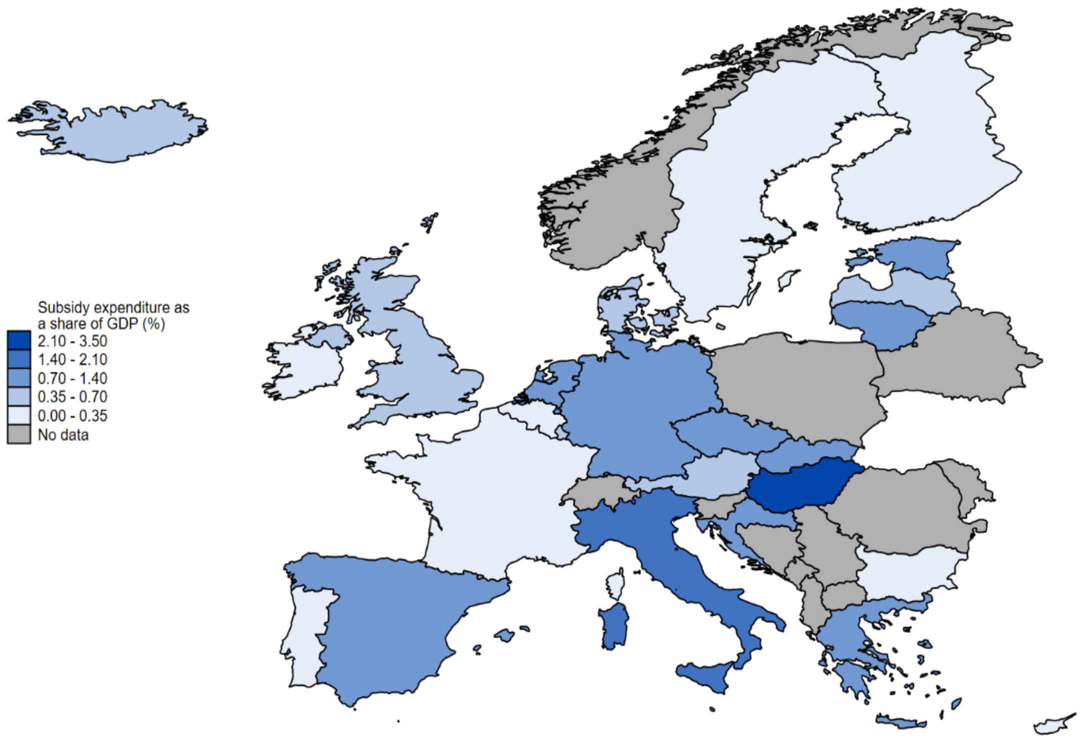
Source: industrial policy spending type data is from the OECD's Quantifying Industrial Strategy *(QuIS, 2019-2022)*. The number of types in the same sector allows for combinations across the 2019-2022 period. Countries included: Denmark, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, United Kingdom.

2.47 Figure 2.7 considers only direct subsidies, using data from the EU State Aid database from 2016 to 2023, and the UK Subsidies database from 2021 to 2023 (data for Spain, where included in EU comparisons, comes from the separate Spanish State Aid database).

2.48 With less than 0.7% of GDP spent on subsidies, the UK lies at the lower end of the distribution of European countries. Some European countries spend more than twice as much relative to their GDP.

Figure 2.7: The UK spends less on direct subsidies than most EU countries

Direct subsidies as a share of GDP, UK and European peers, 2021-2023, from the EU State Aid, UK Subsidy and Spanish State Aid databases



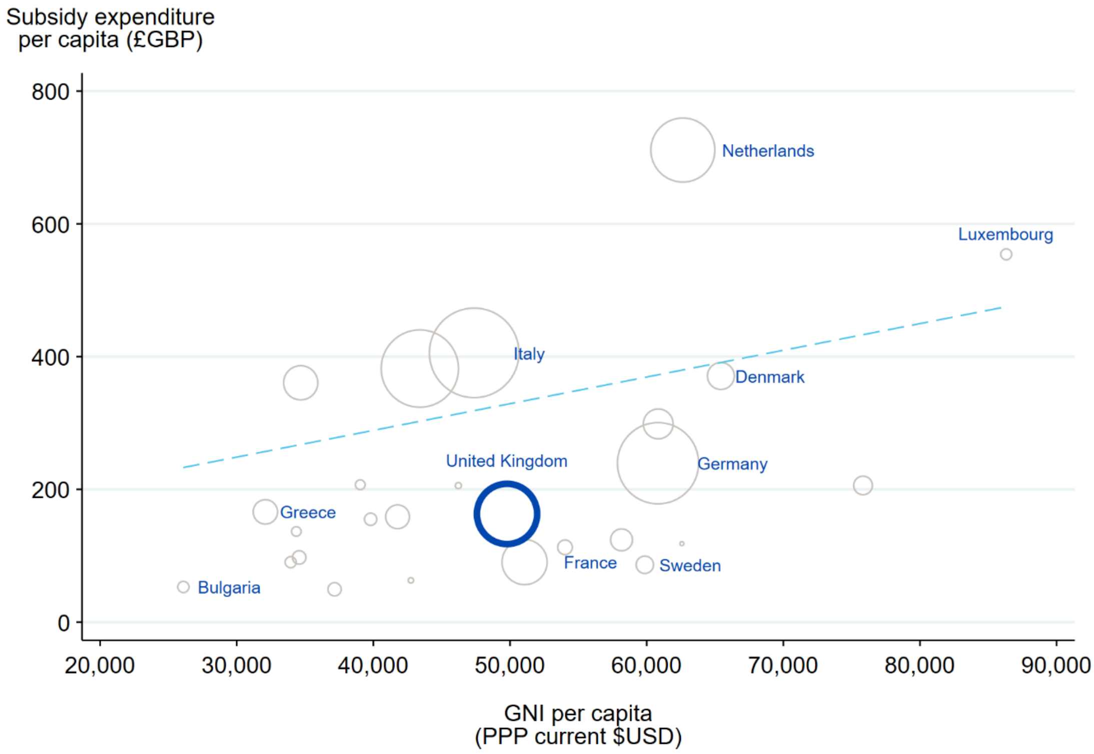
Average subsidy expenditure as a share of GDP (2021-2023) across 26 European nations. Subsidies provided for capitalisation of the UK Infrastructure Bank and COVID-19 support are excluded. Sources: *EU State Aid Database* (2021-2023); *UK Subsidy Database* (2021-2023); *Spanish State Aid Database* (2021-2023).

2.49 Figure 2.8 shows the relationship between per-capita subsidy spending and per-capita income, at purchasing power parity, for the UK and EU countries.

2.50 Richer countries generally spend more on subsidies, but the increase is much less than proportional to the increase in income. A few countries, such as the Netherlands, Luxembourg and Italy, spend more than their income level would predict.

Figure 2.8: Richer countries spend more on subsidies but there are big outliers

Direct subsidies and per-capita income, UK and European peers, 2021-2023, from the EU State Aid, UK Subsidy and Spanish State Aid databases

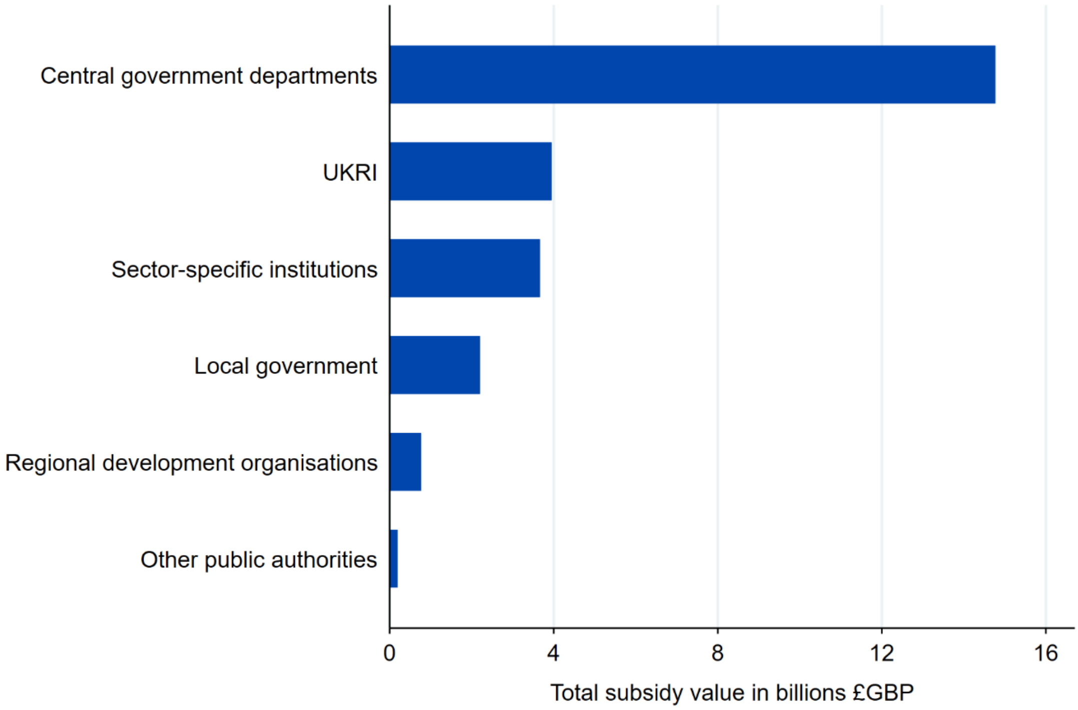


Subsidy expenditure per capita and Gross National Income (GNI) per capita averaged from 2016-2023 for 26 European nations. Each marker size reflects the relative size of each countries' total subsidy expenditure for 2016-2023. Countries analysed include: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Spain, Sweden and the United Kingdom. Sources: *EU State Aid Database* (2016-2023); *UK Subsidy Database* (2021-2023); *Spanish State Aid Database* (2016-2023); *World Bank Development Indicators* (2016-2023).

2.51 Within the UK, central government departments are by far the largest source of subsidies, with roughly £15bn disbursed (see Figure 2.9). UK Research and Innovation (UKRI) and sector-specific institutions (such as Visit Scotland, Tourism NI and Energy Transition Zone Limited) follow with around £4bn, with local government, regional development authorities and other public bodies jointly making up another £4bn.

Figure 2.9: Central government departments are by far the largest source of UK subsidies

Subsidy spending by source, UK, 2016-2023, from the EU State Aid and UK Subsidy databases



Total value of subsidies awarded in the UK (2016-2023) disaggregated by awarding public authorities. Subsidies provided for capitalisation of the UK Infrastructure Bank, Contract for Difference awards and COVID-19 support are excluded. Public authorities are ranked by the highest total amount of subsidies in the period. Sources: *EU State Aid Database* (2016-2023); *UK Subsidy Database* (2021-2023).

2.52 In this chapter, we have provided new evidence on how existing UK industrial policies compare to those of peer countries in terms of spending levels, use of financial instruments and favoured industries. The next chapter focuses on what we know about the impact of these policies on outcomes policymakers seek to influence, such as productivity, employment, and innovation.

3. What are the overall effects of industrial policies?

3.1 Estimating the average effect of industrial policies is difficult. As noted by Juhász, Lane and Rodrik, industrial policies are correlated with outcomes of interest by design: they are enacted precisely to affect specific outcomes in a targeted way.

3.2 Governments implement industrial policies for various reasons: to raise overall productivity, to establish a toehold in a strategically important industry, or to support places that otherwise might be left behind by the modern economy.

3.3 We would expect policies enacted for these distinct reasons to affect productivity, employment, and innovation differently, but usually cannot tell what policy was chosen for what purpose. This makes evaluating "success" difficult.

3.4 For instance, Coyle and Alayande conduct a case study of three UK industries (life sciences and pharmaceuticals, finance and the creative industries) since 1980 and argue that despite the absence of a coordinated, long-term industrial strategy, these sectors have been exposed to industrial policies "by accident".

3.5 Coyle and Alayande conclude that a more deliberate industrial strategy would have led to better productivity and investment outcomes by increasing policy coordination, de-risking investment and increasing the potential productivity spillovers.

3.6 Moreover, as we show in Chapter 2, different countries choose different combinations of policies at different times. These too may affect outcomes of interest differently. Chapter 4 will examine these differential effects in more detail.

3.7 In this chapter, we first strip out other factors that might lead industrial policies and outcomes of interest to be systematically correlated in a particular way, not directly related to the effect of the policy in question.

3.8 We show that on average, industrial policies in the OECD since 2019 target industries that already have higher productivity and higher employment than comparison industries (a *selection* effect). A superficial look at the evidence might therefore lead us to attribute these productivity and employment differences to industrial policies, when in fact they pre-date them.

3.9 We then use the timing of industrial policy changes to better tease out the direction of influence: how much does the relationship between industrial policy spending and our outcomes of interest change *after* the introduction of industrial policies, compared to before? We run regressions against outcomes for several years before and after the policy change and show the discrete change (where there is one) relative to the timing of any policy changes (this brings us closer to a causal *treatment* effect of industrial policy).

3.10 For our period of study, we find a small, positive effect of increased industrial policy spending on labour productivity in the targeted sector (in most regression specifications not significant at conventional significance levels), and no effect on employment. The latter is not necessarily surprising as some targeted industries may shed employment as they become more productive, and others may add employment.

3.11 Labour productivity can rise via either higher capital intensity (through higher investment) or increases to total factor productivity (for instance, through technological progress).

3.12 We therefore also investigate the impact of industrial policies on investment and research and development (R&D) spending and do not find an effect. This suggests the effect of industrial policy on labour productivity may operate by making firms more efficient rather than through capital deepening.

3.13 Due to data constraints, we can only examine effects of industrial policies over a two-year horizon. Longer-term studies may detect further effects.

3.14 Finally, for a subset of countries we can look at the effect of industrial policies on cost markups, a measure of market power. Additional industrial policies do not raise market power. This suggests that industrial policy and competition policy may not necessarily be in conflict.

Industrial policies have tended to target higher-productivity industries

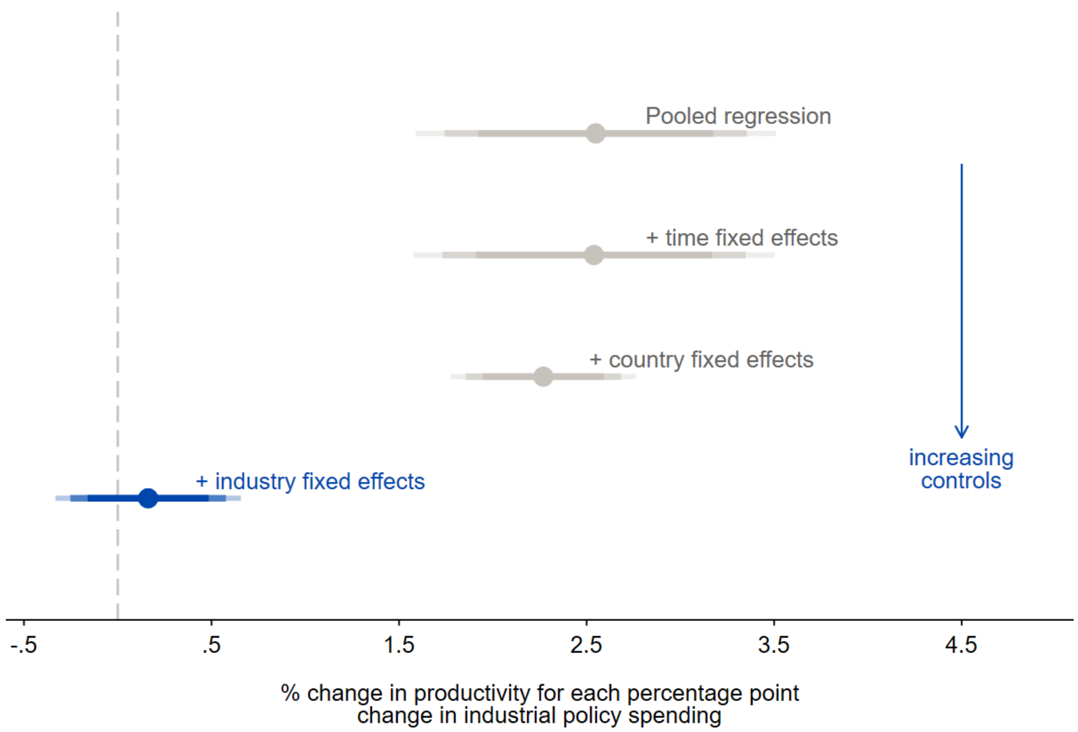
3.15 To investigate the effect of industrial policies on outcomes of interest, such as productivity, employment, and innovation, we ask how changes to industrial policies in one industry, country and year are related to outcomes in the same industry and country in subsequent years.

3.16 We undertake this exercise with both industrial policy spending from the QuIS database (for a total of ten countries), and industrial policy counts using the GTA database (for a total of thirty-three countries). The former gives us a more precise measure of industrial policy, but the latter is available for more years, countries, and industries.

3.17 To make this comparison more like-for-like, we progressively remove differences in outcomes not related to industrial policies. Figure 3.1 shows this process for our baseline QuIS regressions, with labour productivity as the outcome, in the year following a policy change.

Figure 3.1: Industrial policies tend to target more productive industries, where they can have small positive effects

Coefficients from regressions of labour productivity on industrial policy spending, 2019-2022, from QuIS and the OECD national accounts database



Robust standard errors. Labour productivity defined as Gross Value Added (GVA) divided by amount of hours worked. Included countries: Canada, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Source: *OECD* (2019-2022) and *Quantifying Industrial Strategies* (2019-2022).

3.18 From the top to the bottom, we progressively include common time effects, common country effects and common industry effects. Figure E.3 in the appendix shows the same exercise with clustered standard errors at the industry by country level, while Figure E.4 shows results of our GTA regressions.[3]

3.19 The estimated effect of industrial policy spending drops considerably once we include industry fixed effects. This suggests that industrial policies tend to

[3] Appendix F contains the underlying regression tables for all regression results shown in the main body of this report.

target higher-productivity industries, and failing to account for this would lead us to overestimate the productivity effects of industrial policies.

3.20 In our strictest specification, accounting for time, country and industry factors, a one percentage point increase in industrial policy spending as a share of GDP leads to about a 0.25% increase in labour productivity in the targeted industries.

3.21 A few additional caveats apply. First, we cannot estimate the effect of any industrial policies that are not sector-specific, because we implicitly compare industries that receive more industrial policy spending with those that receive less. 68% of industrial policy spending in the QuIS database is not sector-specific. To the extent that the effect of these policies is different, we cannot distinguish it.

3.22 Second, since we use industry-level data at relatively high levels of aggregation, and the existing panel is still quite short, the analysis suffers from low statistical power. With more data, perhaps we could more confidently rule out null effects. This is particularly true for some outcomes, such as investment, where data is not available for all industry by country by year observations.

Industrial policies on average have generally had modest positive effects on productivity

3.23 Even accounting for time, country and industry factors, there is still a risk that the analysis picks up a spurious relationship between industrial policies and productivity.

3.24 A stricter test is to run these regressions for years before and after the policy change. We do not expect industrial policies to affect outcomes before they come into effect, so a discrete change after the policy is implemented would increase our confidence that the results are indeed driven by the policy we study.

3.25 On the other hand, one might expect industrial policies to take several years to fully influence outcomes of interest, creating the risk that we underestimate the full impact. In a study of place-based EU policies, Fritz and Van der List for instance look at outcomes over a seven-year period. Even over this period however, they often find negligible results.

3.26 Given the nature of the data we use, we can only estimate the effect over a two- to three-year period. To the extent that longer-run effects are larger than short-run effects, our results are therefore an underestimate.

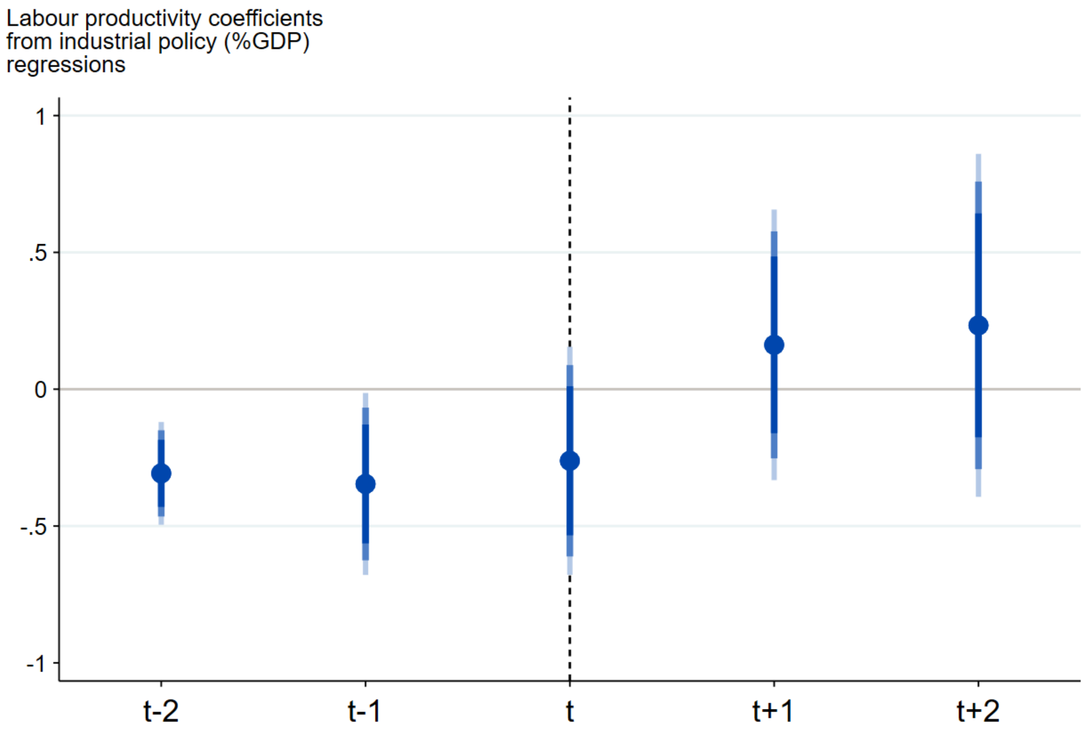
3.27 Figure 3.2 shows the outcome of this quasi-event study for labour productivity, for two years before and two years after a policy change.

3.28 The coefficient of interest is generally below zero before the policy change (suggesting that after removing common year, country and industry factors, industrial policies target industry-country-year instances that are slightly less productive than comparison observations). This means that removing industry selection effects may slightly overcorrect for positive selection on productivity.

3.29 After the policy is enacted, the coefficient of interest is small and positive (though never statistically significant). Results are similar with clustered standard errors, as Figure E.5 shows, and an alternative approach using local projections yields very similar results.

Figure 3.2: Industrial policy spending is followed by small productivity gains

Coefficients from regressions of labour productivity on industrial policy spending, 2019-2022, from the OECD national accounts database



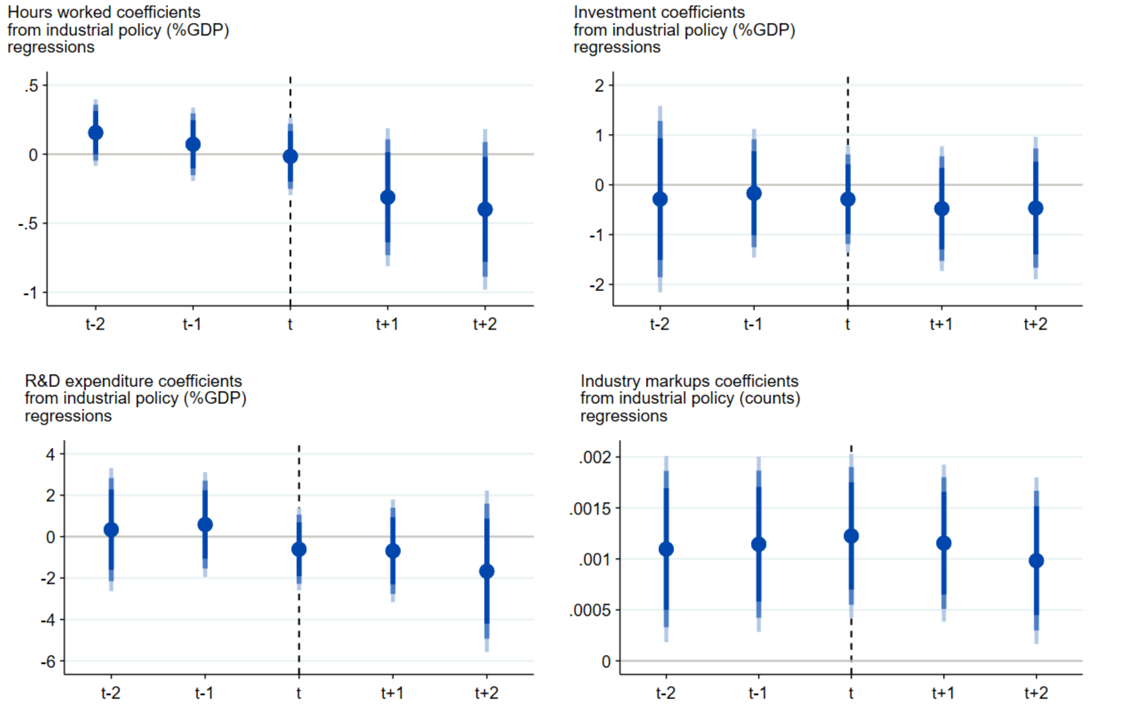
Time, country and industry fixed effects included, robust standard errors. Labour productivity defined as Gross Value Added divided by amount of hours worked. Included countries: Canada, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Sources: *OECD* (2019-2022) and *Quantifying Industrial Strategies* (2019-2022).

Industrial policies on average have had no clear effect on industry employment, investment, R&D, or market power

3.30 Figure 3.3 repeats this exercise for four additional outcomes: employment, investment, R&D, and markups. Because investment, R&D and markups are not observed for all industries, countries and years in a consistent way, our ability to detect effects is even smaller than for our baseline productivity and employment results.

Figure 3.3: There is no clear effect of industrial policy on employment, investment, R&D or markups

Coefficients from regressions of (1) hours worked, (2) investment, (3) R&D and (4) markups on industrial policy spending, 2019-2022, from the OECD national accounts database and CompNet, 2010-2022



Time, country and industry fixed effects included, robust standard errors. For panels 1-3 we use industrial strategy data from *Quantifying Industrial Strategies* (2019-2022). Included countries: Canada, Denmark, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Hours worked, investment and R&D data are from *OECD* (2019-2022). Panel 4 uses industrial policies counts as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data (2010-2022). Included countries: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Latvia, Lithuania, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the UK. Markup comes from *CompNet database* (1997-2021) and is estimated using the production function approach (Ordinary Least Square estimation of a translog production function, with materials as flexible input). Top and bottom 1% markups in each year have been excluded.

3.31 As Panel A of Figure 3.3 shows, we do not see any significant changes to industry employment after an increase in industrial policy spending at any conventional significance levels. Likewise, we do not see significant changes in investment, R&D, and markups[4] over a two-year period, as can be seen in Panels B, C and D. The same holds true for concentration, as Figure E.6 in

[4] For international competition measures at the industry-country-year level, we use data from the Competitiveness Research Network (CompNet). CompNet constructs these measures from national firm-level microdata. The overlap between CompNet and our baseline data is not perfect, resulting in a slightly smaller final dataset.

the appendix shows, and when standard errors are clustered by country and industry as shown in Figure E.7 and Figure E.8.

3.32 This null effect may be surprising in the light of industry-specific studies that variously find positive effects on investment, employment, or R&D. On closer reflection however, it is perhaps less surprising.

3.33 First, we estimate the effect of the average policy. Individual policies are often carefully designed to achieve a particular outcome (for instance, to raise R&D) but may not lead to changes on other outcomes.

3.34 Second, policies often target a small subset of the firm population. Therefore, where firm-level studies might find effects, at the industry level these effects might not be detectable. Finally, given the short time coverage and aggregated industry data, we lack the statistical power to detect small effects.

3.35 The absence of large effects is in line with existing evidence, as summarised for instance in Criscuolo, Gonne, Kitazawa and Lalanne. The authors find mixed evidence at best for the effectiveness of grants and subsidies, though they argue that targeted R&D programmes are effective at increasing R&D expenditure in affected firms.

3.36 Further evidence of the potential effectiveness of targeted R&D programmes is provided by Dechezleprêtre, Einiö, Martin, Nguyen and Van Reenen, who find large effects from a UK R&D subsidy scheme on small firms. They estimate an increase in both R&D spending and patenting activity equivalent to a 10% increase in aggregate R&D spending and argue that this innovation activity had further spillover effects.

3.37 Studies focused on individual industries sometimes find larger effects. For example, Barwick, Goldberg, Kwon, Li and Zahur in their study of the global electric vehicle market find that consumer subsidies are effective at raising electric vehicle demand and economic surplus.

3.38 However, they find that this positive effect is dampened by local content requirements because it can divert production to less efficient domestic manufacturers.

3.39 By contrast, while Kantor and Whalley find that public R&D during the US space race increased manufacturing value added, employment and investment in space-related industries, the effects are moderate in magnitude at both the local and national level.

3.40 Likewise, Barwick, Kalouptsidi and Zahur study Chinese efforts to boost its shipbuilding industry via industrial policies, and find mixed effects at best.

While the policy increased China's domestic investment, firm entry, and its international market share, it also led to low returns, a fragmented industry and idle capacity.

3.41 The authors conclude that while some industrial policies worked well in this context (notably production and investment subsidies), others (such as entry subsidies) were wasteful. Finally, they argue that better targeting and counter-cyclical policies could possibly have prevented some of the distortions introduced by the policy.

3.42 In this chapter, we have shown that on average industrial policies tend to target larger and more productive sectors. This is a selection effect rather than a causal "treatment" effect.

3.43 Once we account for this, the average increase in industrial policy spend is associated with a small but positive subsequent increase in labour productivity, and on average no measurable increase in employment, investment, R&D, or markups.

3.44 But averages may disguise as much as they show. Existing studies of specific policies and specific industries sometimes find larger effects, suggesting that industrial policies need to be carefully designed to achieve the desired outcomes.

3.45 In the next chapter, we investigate to what extent industrial policies have different effects if targeted at different sectors, or via different instruments.

4. How do effects differ by instrument and sector?

4.1 In previous chapters we have shown that different countries use different industrial policies in different circumstances, and that the average effect on productivity and other outcomes of interest for the average industrial policy is very modest in size.

4.2 In this chapter, we split out different tools and different target sectors to provide some evidence on their relative impacts. Tax credits appear to have the biggest positive impact on productivity in the targeted sectors, followed by state loans and loan guarantees. Industrial policies also appear to be more effective in production (that is, manufacturing, mining and utilities) than services.

4.3 These differences are important for policy design. They support the UK's historical preference for tax credits and have implications for the selection of the growth-driving sectors, which feature both manufacturing and services industries.

Tax credits appear to be the most effective instrument for raising productivity in the targeted sectors

4.4 Figure 4.1 shows separately the effects of different industrial policy instruments, using data from the GTA database. Tax reliefs have quantitatively the largest effect on labour productivity, followed by state loans and loan guarantees. Coefficients on other instruments are quantitatively small and not significant.

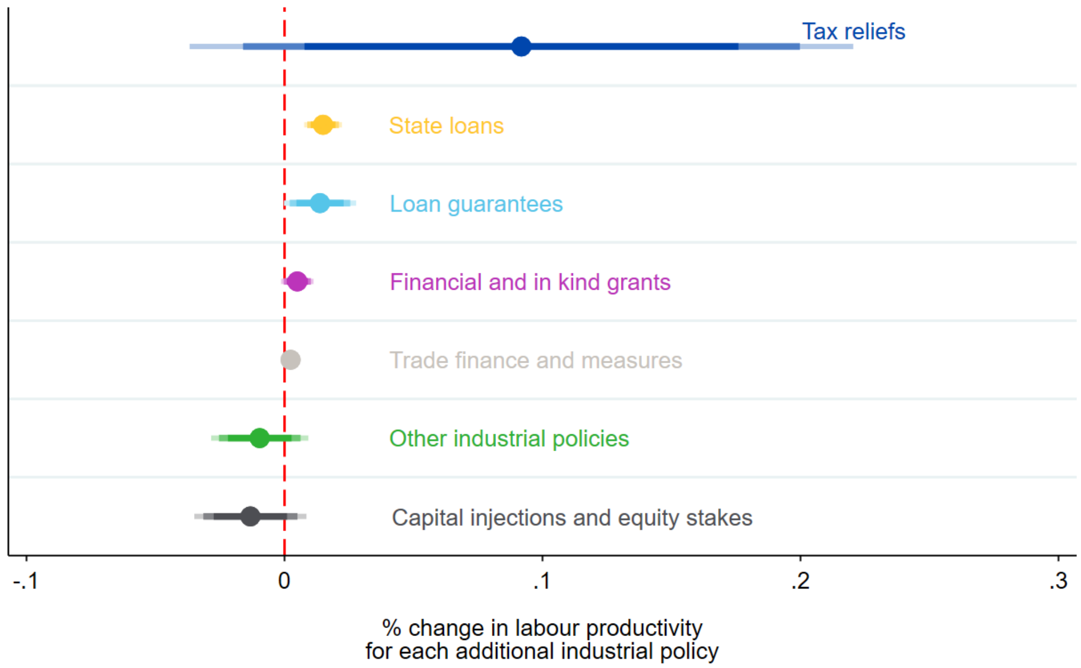
4.5 In terms of magnitudes, the introduction of an additional tax relief policy has about ten times the effect of the introduction of most other industrial policies. Results are not substantially different when standard errors are clustered at the country by industry level, as shown in Figure E.9 in the appendix.

4.6 Tax reliefs are not only characterised by a larger effect size, but also by wider confidence intervals. This reflects the fact that the GTA database contains a relatively small number of tax relief measures, compared to other industrial policy instruments (see Figure E.10 in the appendix).

4.7 As with the average industrial policy effect, one must be careful to distinguish selection effects from potential treatment effects. If tax credits are given predominantly to help growing firms expand, and capital injections are given to struggling firms to survive, not all the observed difference is due to the industrial policies.

Figure 4.1: Tax credits appear to be most effective at raising productivity

Coefficients from regressions of labour productivity on industrial policy count, by instrument type, 2019-2022, from the OECD national accounts database



Time, country and industry fixed effects included, robust standard errors. GTA instrument category coefficients from separate regressions. Labour productivity defined as Gross Value Added divided by amount of hours worked. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Sources: *Global Trade Alert* data (2010-2022) and *OECD* (2010-2022)

4.8 Figure E.11 in the appendix shows the quasi-event study plots for tax credits and capital injections, respectively. Some of the differences seem to predate the introduction of the policy and therefore are likely selection effects. Further differences appear after the introduction of these policies. This suggests that perhaps some of the productivity differences attributed to different tools may indeed be due to the policies themselves.

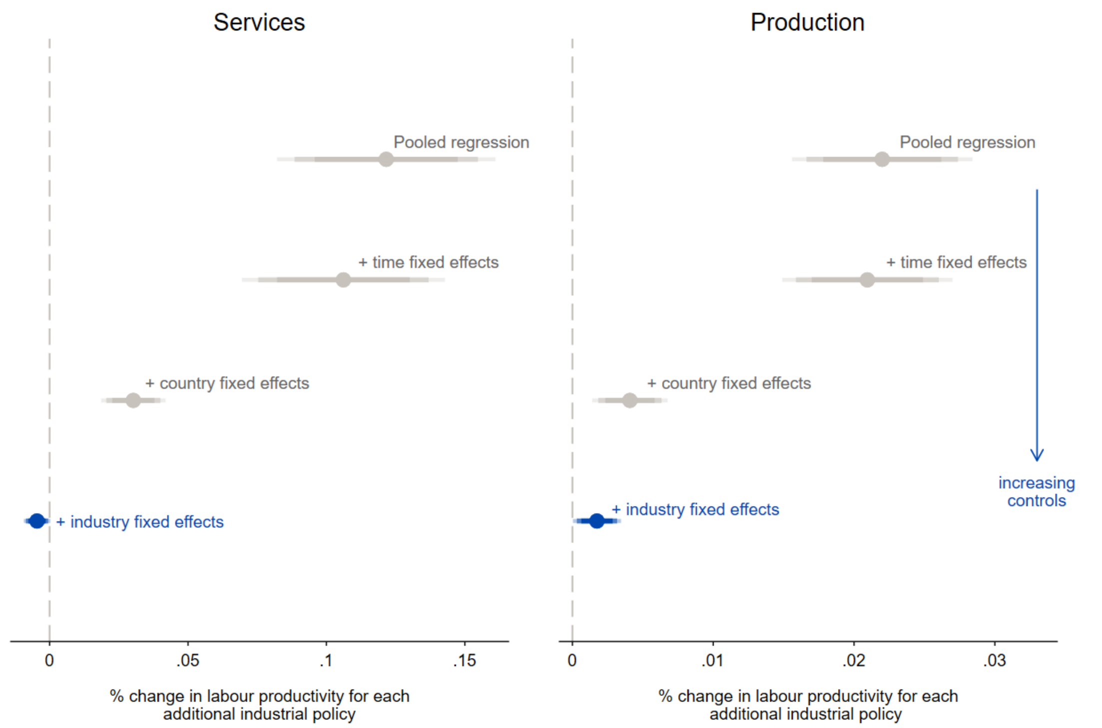
Industrial policies are more strongly related to productivity in production than services

4.9 Figure 4.2 splits the effect by services versus production (which includes manufacturing as well as the utilities). The whole-economy average effect seems to be driven by production (where the effect is positive and significant) rather than services (no effect). This is consistent with the observation in Juhász, Lane and Rodrik that industrial policy traditionally targets production and not services, but the same caution regarding selection versus treatment effects still applies. Figure E.12 shows results with clustered standard errors.

4.10 By contrast, Manelici and Pantea are among the first to provide evidence of a service-targeted industrial policy (specifically, a tax break for Romanian IT workers) and find large and persistent effects on firm growth.

Figure 4.2: Industrial policies are positively related to productivity in production but not in services

Coefficients from regressions of labour productivity on industrial policy spending, for services and production, 2019-2022, from the OECD national accounts database



Robust standard errors. Labour productivity defined as Gross Value Added divided by amount of hours worked. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Sources: *Global Trade Alert* (2010-2022) and *OECD* (2010-2022).

4.11 This chapter has disaggregated average industrial policy effects across different tools and by the sector they target. Tax credits appear to be associated with the biggest positive productivity increase in subsequent years. Based on the evidence considered here, industrial policies also appear more successful when targeted at production than at services. These findings suggest that the careful choice of industrial policies tools and sectors can affect how much an industrial strategy raises productivity.

4.12 In the next chapter, we investigate the regional distribution of past industrial policies, as well as the regional impacts on productivity and employment.

5. What are the regional effects of industrial policies?

5.1 Because industries are not distributed evenly across regions, industrial policies are, wittingly or unwittingly, also place-based policies. This chapter examines the regional distribution of direct subsidies, and the regional impacts of wider industrial policies.

5.2 We show that subsidies play a larger role, relative to regional GDP, in Wales and Yorkshire and the Humber. For Northern Ireland, the East Midlands and the South East, subsidies are a much smaller share of the regional economy.

5.3 We examine the regional effects of industrial policies on labour productivity and employment. To estimate these effects, we use the uneven exposure of regional economies to different industries, coupled with national industry-level shifts in industrial policy.

5.4 For labour productivity, we get comparable results to our industry-level regressions in Chapter 3. An additional industrial policy increases regional labour productivity by roughly 0.5% over the following two years.

5.5 In contrast to our industry-level results, regional employment coefficients also show a small but statistically significant increase after a policy's introduction. This could be due to regional spillover effects, or employment shifting across regions.

Wales and Yorkshire and the Humber have received the largest share of subsidies relative to the size of their economy

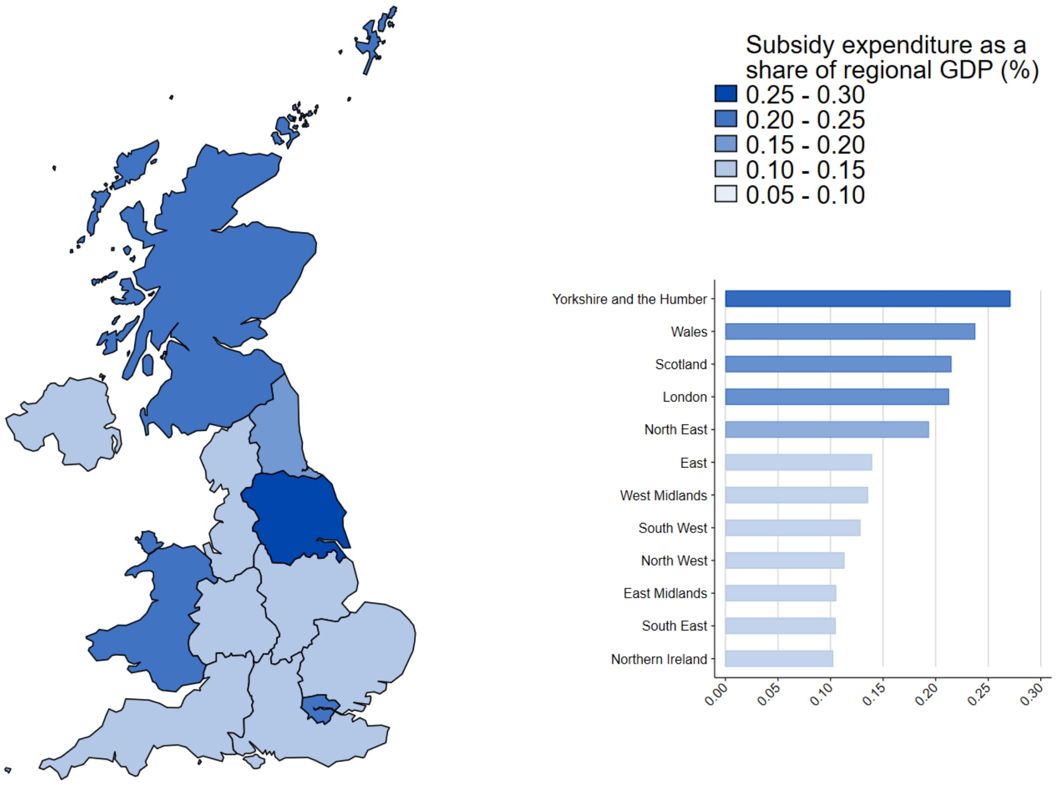
5.6 There are multiple ways to assess the regional impact of subsidies. We can look at total amounts or subsidies per capita (Figure E.13-Figure E.16 in the appendix). Here, we look at subsidies relative to regional GDP. This gives a sense of how important subsidies are for the regional economy.

5.7 Figure 5.1 shows the results for the devolved nations and large regions of England. Yorkshire and the Humber receives the largest share of subsidies relative to the size of the regional economy, followed by Wales, Scotland, and Greater London. Northern Ireland, the East Midlands and the South East receive the least, about half of the amount Wales and Yorkshire and the Humber receive relative to their GDP.

5.8 Figure E.17 in the appendix shows that large subsidies (over £100 million) account for a relatively larger share in Yorkshire and the Humber than in the rest of the UK.

__Figure 5.1: Wales and Yorkshire and the Humber have received a higher share of subsidies relative to their regional economies__

Subsidies as a share of regional GDP, UK, 2021-2022, from the EU State Aid and UK Subsidy database and ONS regional accounts



UK regions' average subsidy expenditure as a share of GDP (2021-2022). Subsidies provided for capitalisation of the UK Infrastructure Bank and Contract for Difference awards are excluded. Sources: *EU State Aid Database* (2021-2022); *UK Subsidy Database* (2021-2022); *ONS Regional Accounts* (2021-2022).

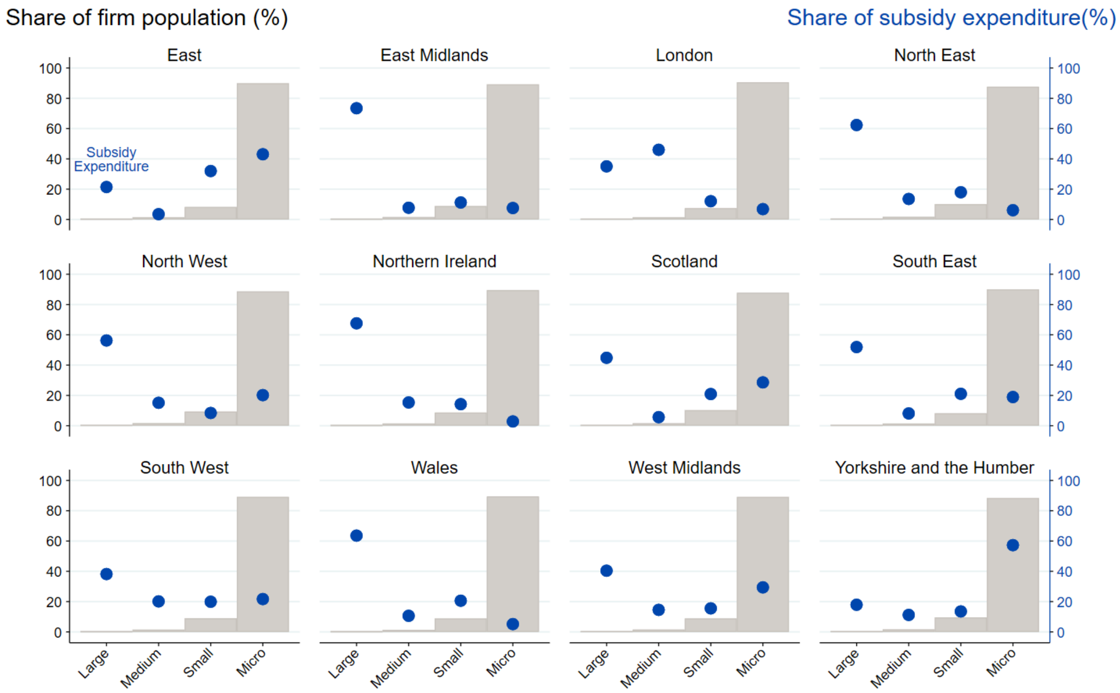
5.9 Across regions, subsidies also go to different firms. Figure 5.2 shows the regional firm size distribution in grey against the distribution of subsidy recipients in blue. The firm size distribution looks similar in most parts of the UK and is dominated by micro-firms.

5.10 Subsidies on the other hand predominantly go to large firms, though there are some exceptions: in the East and Yorkshire and the Humber, micro-firms are the most common recipients; in London, most subsidies go to medium-sized enterprises. Once we exclude large subsidies (over £100 million), large firms account for the largest share of subsidies everywhere (see Figure E.18 in the appendix).

5.11 Other researchers have studied the effect of giving regional subsidies to different types of firms. For instance, Cingano, Palomba, Pinotti and Rettore examine a large programme of investment subsidies in Italy. Using the cutoff rules according to which funding is allocated, they find that subsidies increase the marginal recipient's investment by 39% and their employment by 17% over the following six years.

Figure 5.2: In most but not all regions, subsidies tend to go to large firms

Firm size distribution and subsidy distribution, by UK region, 2021-2023, from the UK Subsidy database and ONS business data



Share of business population and subsidy expenditure (2021-2023) disaggregated by firm size (employment sizebands) across UK ITL1 regions. Analysis excludes the £22 billion subsidy provided for capitalisation of the UK Infrastructure Bank, Contract for Difference awards and COVID-19 support subsidies. Sources: *ONS Business Workbooks* (2021-2023); *UK Subsidy Database* (2021-2023).

5.12 Younger and larger firms and those scoring higher in the programme application created more employment per euro spent. Those favoured by local politicians on the other hand created fewer jobs per euro spent.

5.13 According to the study, moving away from objective rules to political discretion would have been 55% more expensive, and particularly costly in Southern Italy, which received the largest share of funds and had the highest per-job costs.

Regional exposure to industrial policies varies more across countries than within

5.14 Existing data sources only measure exposure to industrial policies at the national level, but we can infer regional exposure by examining where recipient industries are located geographically.

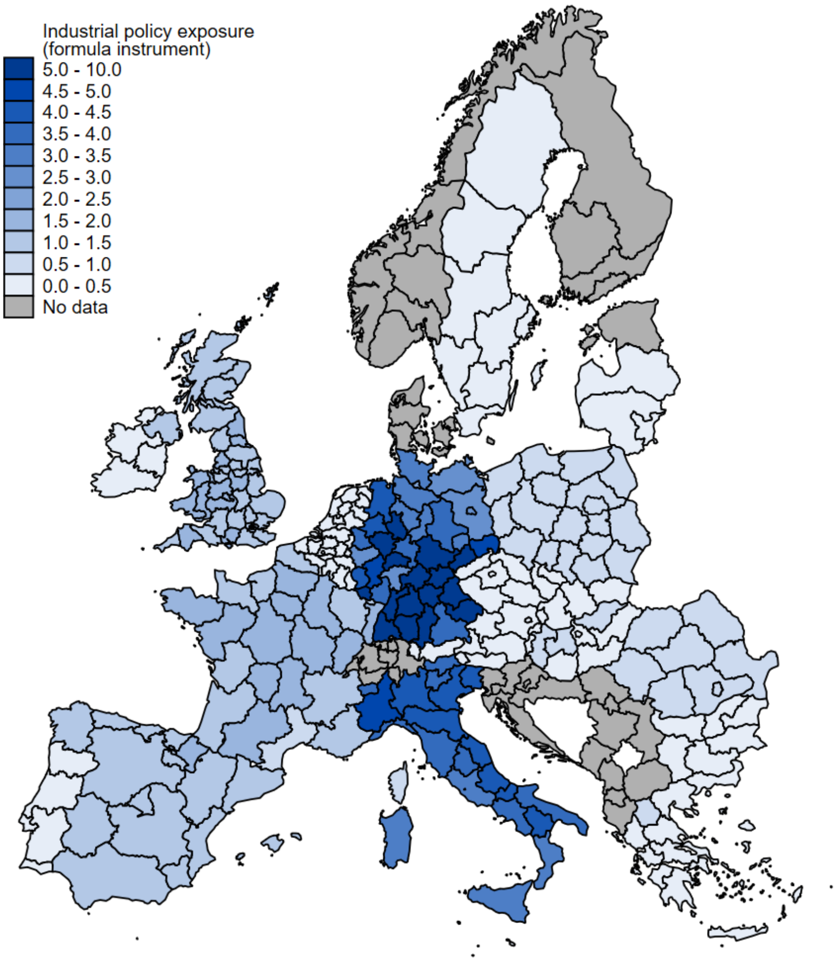
5.15 To do so, we compute regional employment shares in each industry, and multiply these by the national, industry-level policies. Of course, to the extent that there are within-industry differences across regions, we are unable to detect them.

5.16 In other words, our data cannot capture cases where, for instance, manufacturing firms in the North East are more likely to receive industrial policy support than manufacturing firms in the South West.

5.17 Figure 5.3 shows how our measure of regional industrial policy exposure looks for Europe as a whole. Cross-country differences in industrial policies are generally larger than within-country differences. Within Europe, Southern Germany, the Netherlands, and Northern Italy are some of the largest beneficiaries of industrial policies. Portugal, Sweden, and the Baltic countries have uniformly low exposure to industrial policies.

Figure 5.3: Southern Germany and Northern Italy are among the largest industrial policy beneficiaries

Regional exposure to national industrial policies, UK and European peers, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, and Eurostat data

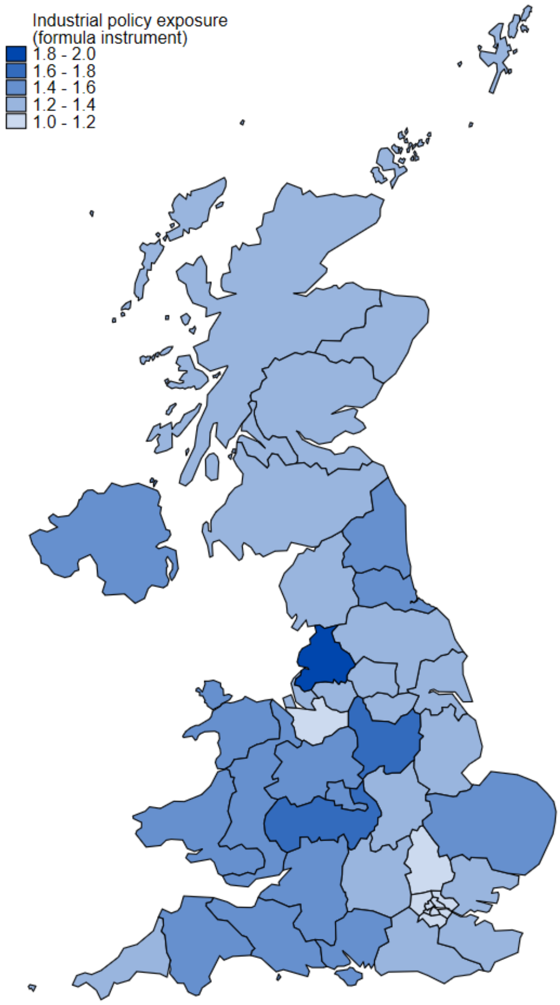


Industrial policy exposure as measured using regional aggregates of 2010 European NACE2 industrial employment shares *Eurostat SBS* (2010) interacted with counts of industrial policies by sector as identified by *Juhász, Lane, Oehlsen and Pérez* (2023) through a machine learning algorithm applied to *OECD Global Trade Alert* data (2010-2022). Included countries: Belgium, Bulgaria, Cyprus, Czechia, Germany, Greece, Spain, France, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and United Kingdom. Iceland, Malta and certain non-mainland NUTS2 territories of Spain, France, Portugal and Norway are excluded. White fill for Kosovo and Bosnia and Herzegovina reflect 'No data'.

5.18 Figure 5.4 zooms in on the UK and replicates the same exercise. Within the UK, Greater Manchester and the West Midlands are most exposed to industrial policies. Greater London on the other hand is the least exposed. This contrasts with regional exposure to the more narrowly-defined subsidies in Figure 5.1, where Yorkshire and the Humber, Wales and Scotland show the highest exposure.

Figure 5.4: Greater Manchester and Merseyside proportionally employ the most people in industries targeted by industrial policies since 2010

Regional exposure to national industrial policies, UK, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, and Eurostat data



UK industrial policy exposure as measured using regional aggregates of 2010 European NACE2 industrial employment shares *Eurostat SBS* (2010) interacted with counts of industrial policies by sector as identified by *Juhász, Lane, Oehlsen and Pérez* (2023) through a machine learning algorithm applied to *OECD Global Trade Alert* data (2010-2022). Due to changes in NUTS2 classifications groups UKI5, UKI6, UKI7 and UKM7, UKM8, UKM9 represent the same underlying employment share data.

Regional exposure to industrial policy has a small but positive productivity and employment effects

5.19 In Chapter 3, we estimate how much industry outcomes of interest change after an industry receives more industrial policy spending.

5.20 Another way to estimate the impact of industrial policies on productivity and employment is to measure the regional exposure to national policy shifts.[5] Different regions will be differentially exposed to industrial policy shifts due to their pre-existing industry composition.

5.21 For instance, a manufacturing-heavy part of the UK (like the Midlands) stands to benefit more from an increase in industrial policy spending targeted at manufacturing than a service-heavy part (like Greater London).

5.22 If national industrial policies are driven by national considerations, selection effects at the local level are mitigated and we can be more confident that local changes to productivity and employment due to exposure to the national policy are indeed caused by it.

5.23 This is the logic of so-called shift-share approaches (developed by Bartik and more recently explained in great detail by Borusyak, Hull and Jaravel), which have been used widely to study industrial policies (see, for example, Elburz and Gezici).

5.24 We therefore compute industry-by-region employment shares (at the NACE2 and NUTS2 level respectively) and apportion national shifts in industrial policy from our industry-level industrial policy counts according to each region's exposure. To remove other, unobserved regional and time differences, we remove regional and time fixed effects (see Figure E.19 in the appendix for additional details).

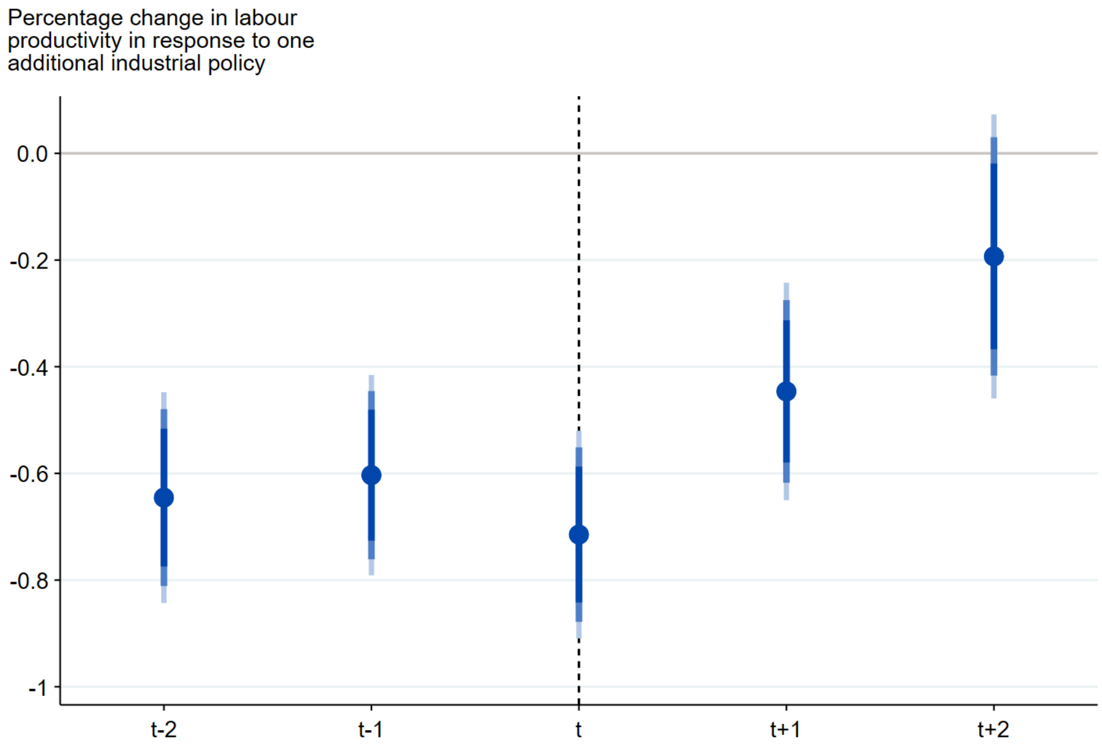
5.25 Figure 5.5 shows the percentage change in labour productivity, estimated at several leads and lags, arising from the implementation of an additional industrial policy. Consistent with the industry-level regressions in Chapter 3, we find a modest and marginally significant increase compared to the pre-introduction coefficients. Results are similar with standard errors clustered at a regional level, as displayed in Figure E.20.

5.26 To give a sense of the size of the effect, regions that are exposed to an additional industrial policy see their labour productivity rise by about 0.5% over the following two years, compared to regions that are not exposed.

[5] Because regional data on investment, R&D and cost markups is not available in the same internationally comparable way, we unfortunately cannot conduct this analysis for all the outcomes in Chapter 3.

Figure 5.5: Regional productivity rises after an increase in industrial policy exposure

Coefficients from regressions of labour productivity on industrial policy exposure, UK and European regions, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, Eurostat and ONS data



Robust standard errors. Labour productivity defined as Gross Value Added (GVA) divided by amount of hours worked. Labour productivity computed using data from *EUROSTAT and ONS* (2010-2022). Industrial policies as identified by *Juhász, Lane, Oehlsen and Pérez* (2023) through a machine learning algorithm applied to *Global Trade Alert* data (2010-2022). Included countries: Belgium, Bulgaria, Cyprus, Czechia, Germany, Greece, Spain, France, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom.

5.27 Figure 5.6 shows the equivalent plot for regional employment. Contrary to the industry-level regressions, this suggests a small but positive effect on regional employment. Results are unaffected when considering standard errors clustered at a regional level, as shown in Figure E.21 in the appendix.

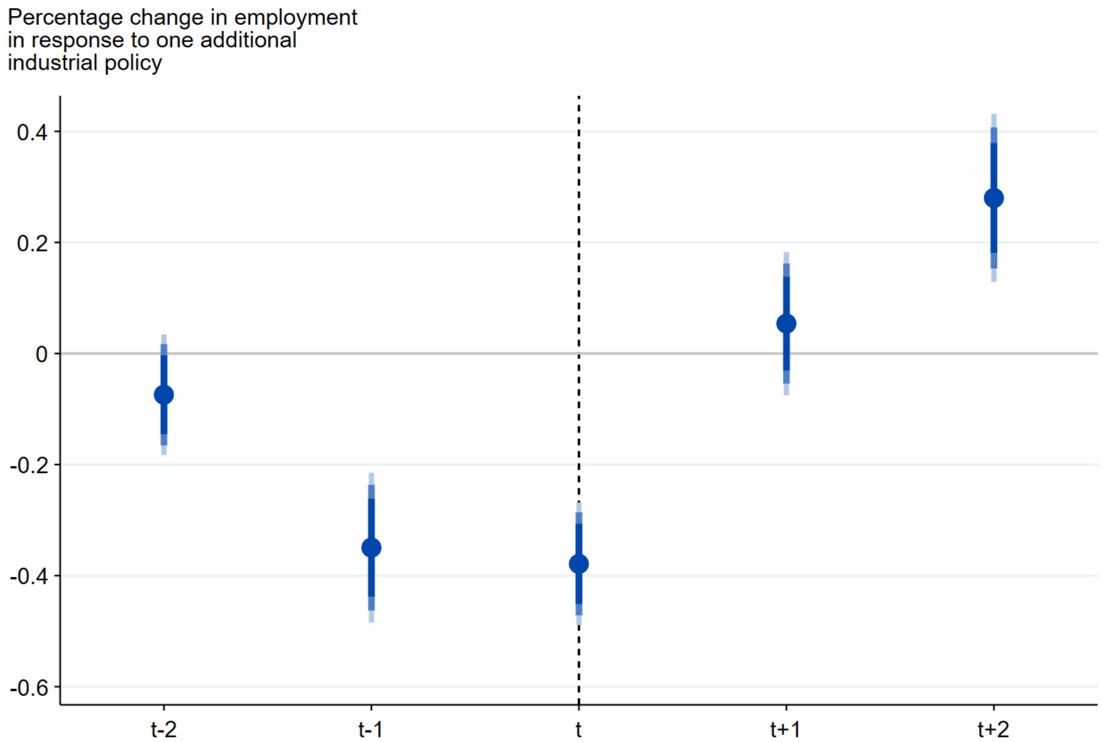
5.28 Employment in exposed regions rises by about 0.7% over the following two years, compared to regions that are not exposed. This is consistent with some existing evidence on place-based policies and local spillovers of industrial policies (see Bartik for a summary).

5.29 In these regional regressions, we implicitly compare regions that see an increase in industrial policy exposure to those that do not. If workers move from non-targeted to targeted regions, we may overestimate the regional employment creation effect. This may explain the difference between our regional employment regressions and their industry-level equivalents in Chapter 3.

5.30 In a recent, UK-based case study, Nathan, Overman, Riom and Sanchez-Vidal examine the relocation of the British Broadcasting Corporation (BBC) from London to Salford. They find that over the following six years, each relocated BBC job creates an additional 0.55 jobs in the creative industries, but overall local employment does not increase. This suggests employment gains in the creative industries come at the expense of other sectors.

Figure 5.6: Regional employment rises after an increase in industrial policy exposure

Coefficients from regressions of employment on industrial policy exposure, UK and European regions, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, Eurostat and ONS data



Robust standard errors. Employment reflects hours worked data from *EUROSTAT and ONS* (2010-2022). Industrial policies as identified by *Juhász, Lane, Oehlsen and Pérez* (2023) through a machine learning algorithm applied to *Global Trade Alert* data (2010-2022). Included countries: Belgium, Bulgaria, Cyprus, Czechia, Germany, Greece, Spain, France, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom.

5.31 Criscuolo, Martin, Overman and Van Reenen estimate the employment and productivity impacts of a specific UK-based regional industrial policy scheme, the so-called Regional Selective Assistance programme. They find that increasing public investment through the scheme by ten percentage points increases local employment by 10%. This effect is driven entirely by small firms. The programme did however not increase productivity.

5.32 Finally, in line with our findings, Criscuolo and coauthors find evidence of selection effects: therefore, looking at outcomes without considering the intent and design of a policy will likely produce misleading estimates.

5.33 Bartik summarises existing research on place-based policies, arguing that they work best when designed to help distressed communities, where both economic and social benefits are largest. The author argues for policies that favour sectors with high agglomeration economies (that is, those that benefit from close geographical proximity of related firms and workers) and those that provide business inputs over direct cash transfers.

5.34 Van der List shows that local labour market power can significantly affect how effective place-based policies are in raising employment. Our earlier report on labour market power in the UK shows that labour market concentration varies significantly across the UK, suggesting that this is another dimension for policymakers to consider.

5.35 Industrial policies can impact different regions differently, both because of explicit place-based objectives, and the natural unevenness of industry distribution across space.

5.36 In the next chapter, we analyse the UK government's recently announced growth-driving sectors in terms of their competitive dynamics, regional exposure, and supply chain linkages. This allows us to speak to the potential industry and regional impacts of the UK government's new industrial strategy.

6. What do we know about the eight growth-driving sectors?

6.1 In its Industrial Strategy Green Paper, the UK government has highlighted eight "growth-driving" sectors: advanced manufacturing, clean energy industries, creative industries, defence, digital and technologies, financial services, life sciences and professional and business services. These sectors were chosen for a number of reasons, including their high productivity levels and export share.

6.2 In our consultation response to the UK government's Industrial Strategy Green Paper, the CMA has emphasised that effective competition policies are productivity-enhancing, and that building competition principles into industrial policies allows policymakers to obtain greater value for money. Piechucka, Sauri-Romero and Smulders have made similar arguments in relation to EU industrial policies.

6.3 At this stage, the UK government has not offered a final definition of the specific industries that constitute each sector. For the analysis in this chapter, we have made our own selection, informed by conversations with experts and stakeholders.

6.4 Using our own sector definitions, we analyse component industries in terms of their size, their competitive dynamics, regional distribution, and their supply chain linkages. We also review the evidence on returns to scale in the growth-driving sectors, as economies of scale are often cited as a reason for industrial policies.

6.5 We find that that overall, the growth-driving sectors are indeed more productive, competitive and dynamic than the whole-economy average. They are more important to UK supply chains and are more likely to produce downstream spillovers.

6.6 Regionally, they are more likely to be located in the South East and around major cities than recipients of current subsidies. Only professional services show evidence of increasing returns to scale, indicating that businesses in the growth-driving sectors are not generally inefficiently small.

6.7 Finally, industries within each growth-driving sector vary widely in their size, productivity, and their competitive dynamics. They also have distinct supply chain and regional footprints that are important to understand both bottlenecks and likely regional impacts. This suggests that any industrial strategy will need to be carefully designed to reap the desired productivity effects.

Competition in the growth-driving sectors at a glance

6.8 This section uses competition metrics computed for the CMA's State of Competition report 2024 to provide an overview of competition in the UK government's growth-driving sectors, relative to the rest of the economy.

6.9 Because measurement of inputs and outputs is problematic in finance and defence, in line with most whole-economy research on competition, and our own State of Competition report, we have omitted these two sectors. We still provide analysis of the employment footprints and supply chain linkages for those two sectors.

6.10 We use three types of competition metrics: first, static competition metrics, that measure market power and concentration at a given point in time. These include cost markups and two often-used concentration measures, the Herfindahl-Hirschman Index (HHI) and the Concentration Ratio of the top ten firms in an industry (CR10).

6.11 Cost markups measure how much firms can raise prices above the cost of producing another unit of output. Concentration metrics measure the share of total industry sales going to the largest firms. For all three measures, a higher number indicates a less competitive industry, all else equal.

6.12 Second, we look at four measures of business dynamism. They capture the fact that the process of creative destruction is crucial to an innovative and growing economy, as argued for instance by Aghion and Howitt.

6.13 These measures are the firm entry and exit rates, the job reallocation rate (which measures the total churn of jobs due to new, growing, shrinking and exiting firms) and how likely the largest firms in an industry are to stay at the top year after year (this measure is called persistence). For the first three measures, higher values indicate a more competitive industry; for the last, a lower value does.

6.14 Finally, we look at three outcome measures of this competitive process. These are the intensity of innovative activity (as captured by spending on research and development, or R&D), the rate of investment, and labour productivity (which measures how much value added the average worker in an industry produces).

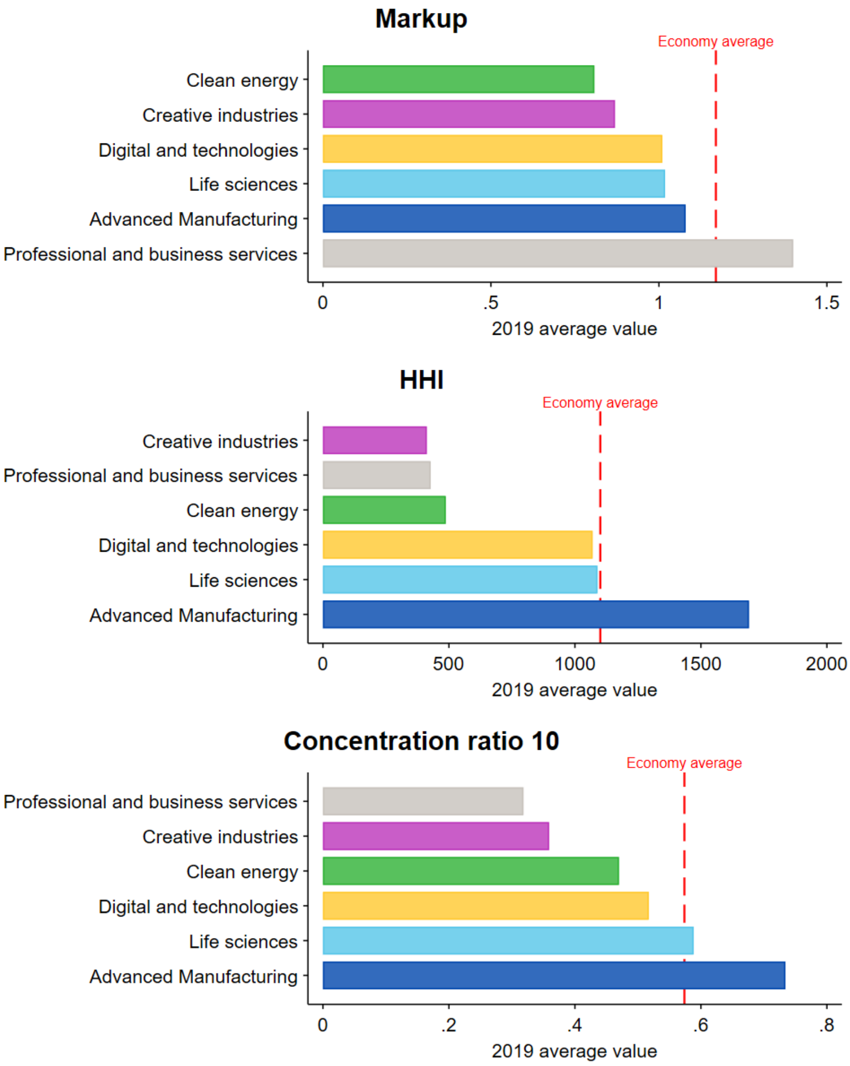
6.15 No one measure can definitively capture whether competition in an industry is working well. Together, they can however paint a picture of its competitive dynamics.

6.16 Figure 6.1 shows the performance of the growth-driving sectors on our static competition measures, relative to the overall economy. Apart from professional and business services, the growth-driving sectors have lower markups than the overall economy. Similarly, only advanced manufacturing is significantly more concentrated than the wider economy.

6.17 Figure E.22 in the appendix looks at the changes in these measures. Many of the key sectors have seen a rise in markups and concentration since 2005. However, markups have fallen in the digital and creative industries, and concentration has fallen in the life sciences and the clean energy sector.

Figure 6.1: Most key growth sectors have lower markups and concentration relative to the economy average

Market power and concentration measures for the growth-driving sectors, UK, 2019, from ONS business microdata



Sectoral averages obtained as turnover weighted averages of all industries included in the sector definition for which we have data. Sources: the *Annual Respondents Database* (1997-2020), the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

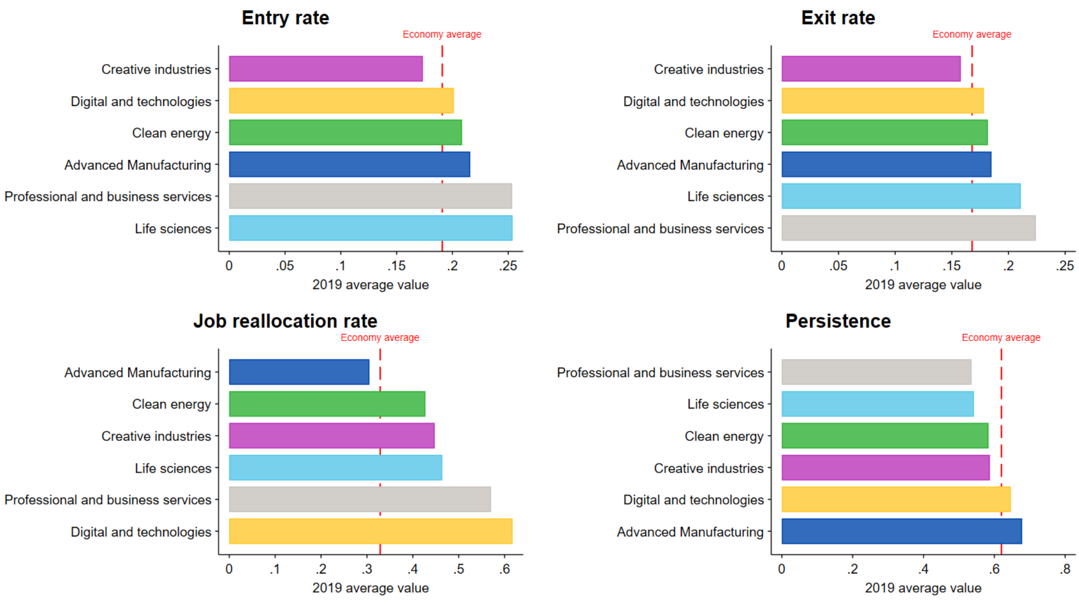
6.18 Figure 6.2 similarly shows how dynamic the growth-driving sectors are. Overall, business dynamism is high in the growth-driving sectors, compared to the whole-economy average.

6.19 Entry and exit rates are above average for all but the creative industries, and job reallocation rates for all but advanced manufacturing. Persistence is generally low (meaning that the firms at the top of each industry come and go), again except for advanced manufacturing and to a lesser degree digital and technologies.

6.20 Figure E.23 in the appendix looks at changes to business dynamism since 2005. Here, the picture is more mixed. Business dynamism has worsened according to at least one of the measures in all growth-driving sectors.

Figure 6.2: Business dynamism is high in the key growth sectors

Business dynamism measures for the growth-driving sectors, UK, 2019, from ONS business microdata



Sectoral averages obtained as turnover weighted averages of all industries included in the sector definition for which we have data. Sources: the *Annual Respondents Database* (1997-2020), the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

6.21 Figure 6.3 examines the competitive outcomes for the growth-driving sectors. Most growth-driving sectors have higher R&D and labour productivity but lower investment rates than the economy overall.

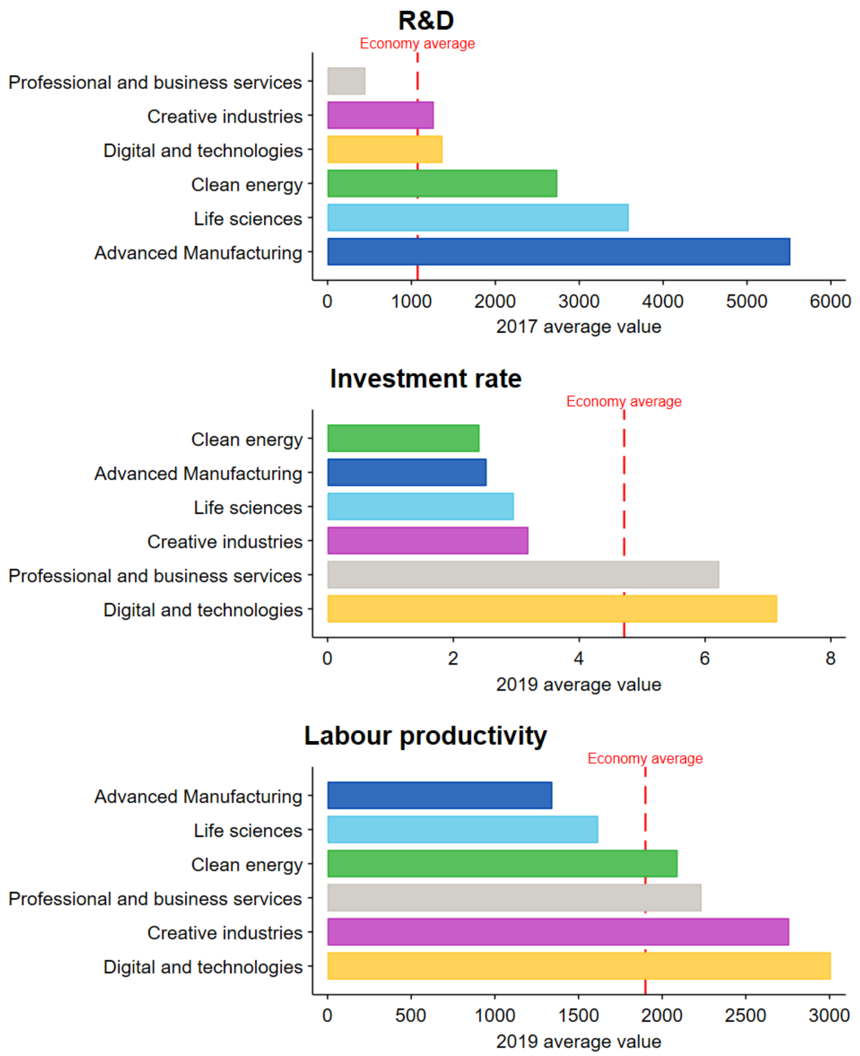
6.22 Exceptions are professional and business services which has low R&D but a higher investment rate than the whole-economy, and digital and technologies which also surpassed the whole-economy investment rate in 2019. Advanced manufacturing and creative industries have lower labour productivity than the whole economy.

6.23 Figure E.24 in the appendix shows the corresponding changes since 2005. Advanced manufacturing, creative industries and life sciences have all seen a decline in their investment rates. Only professional services have increased investment by more than the economy-wide average.

6.24 Except for life sciences and advanced manufacturing, however, the sectors' expenditure trends in R&D have outperformed the whole-economy average. Apart from the creative industries and professional services, the growth-driving sectors have also increased their productivity by more than the overall economy over the past fifteen years.

Figure 6.3: The key growth sectors are typically more productive and innovative but invest less than the rest of the economy

Productivity, innovation and investment measures for the growth-driving sectors, UK, 2019, from ONS business microdata



Sectoral averages obtained as turnover weighted averages of all industries included in the sector definition for which we have data. Economy-wide weighted productivity calculated from SIC 3-digit industries excluding outliers in the top 3%. Sources: the *Annual Respondents Database* (1997-2020), the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

Regional and supply chain characteristics of the growth sectors

6.25 There are many reasons why governments may want to alter the industrial composition of an economy. Where productivity growth is the objective, proponents often invoke two: first, policymakers may hope for regional or supply-chain productivity spillovers into other industries; second, they may believe that returns to scale, scope, or learning bring additional productivity benefits.

6.26 This section shows how the growth-driving sectors are distributed across the UK's regions and nations, and how they are connected to the wider UK supply network. This information can help us understand where productivity spillovers may be most likely.

6.27 Figure 6.4 plots the distribution of employment across the growth-driving sectors. To account for differences in population density, we plot the establishment location quotient, which measures local business establishment concentration compared to the national average.

6.28 The map highlights those ITL3 regions that are in the upper quarter of the distribution of location quotients. Darker shades denote higher regional establishment concentration in growth-driving industries.

6.29 To draw these maps, we need precise data on the spatial distribution of businesses in the growth-driving sector. This is not a simple task. We rely on data from Glass.AI, a company tracking businesses' digital footprint via deep search of information available on the web.

6.30 Chapter 8 compares these estimates to equivalent measures derived from more traditional ONS data and argues that to design and monitor a modern industrial policy, policymakers need access to better business microdata.

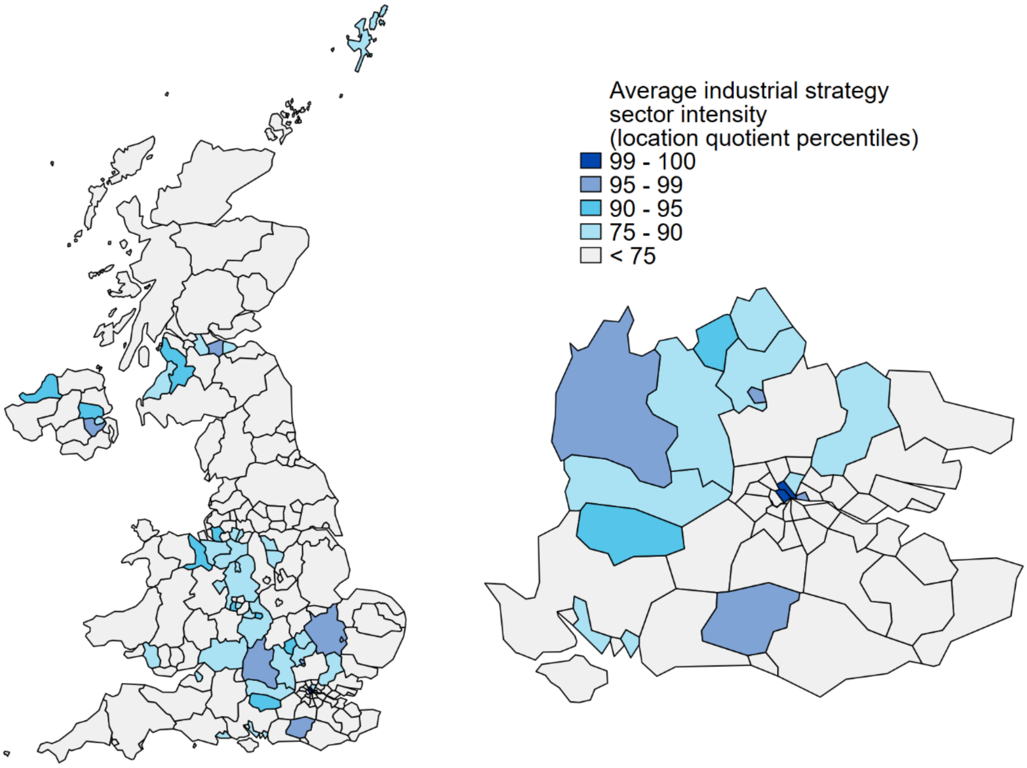
6.31 Figure 6.4 shows that establishments in the growth-driving sectors are particularly concentrated in the South East and the Oxford-Cambridge corridor, with additional pockets in Belfast and parts of Scotland.

6.32 Among existing studies, Mealy and Coyle caution that an industrial strategy that builds on existing regional advantages may entrench or exacerbate existing regional productivity and wage differences.

6.33 The competitive conditions and regional distribution of the targeted sectors themselves are not the only thing that matters for successful industrial policies.

Figure 6.4: Growth sector businesses are concentrated in the South East, the Midlands and parts of Scotland

Establishment location quotients for the growth-driving sectors, UK regions, 2024, from Glass.AI data



Location quotients showing the ITL3 regions in the UK and the South East of England with the highest average concentration of firm establishments in the eight sectors of the industrial strategy green paper. Source: *Glass AI* 2024.

6.34 Liu shows that market failures can propagate upstream via supply chain linkages, compounding as they do so. To correct this distortion, Liu suggests governments may want to subsidise upstream sectors.

6.35 More generally, knowing where target sectors sit in the supply network is important for understanding the impact of industrial policies. For instance, Freeman uses changes in US state-level R&D tax credit to show that firms take into account the innovation costs of their supply chain partners when deciding on their own level of R&D investment.

6.36 Figure 6.5 uses newly released Office for National Statistics (ONS) business-to-business payment flows to understand the location of the growth-driving sectors in UK supply chains.

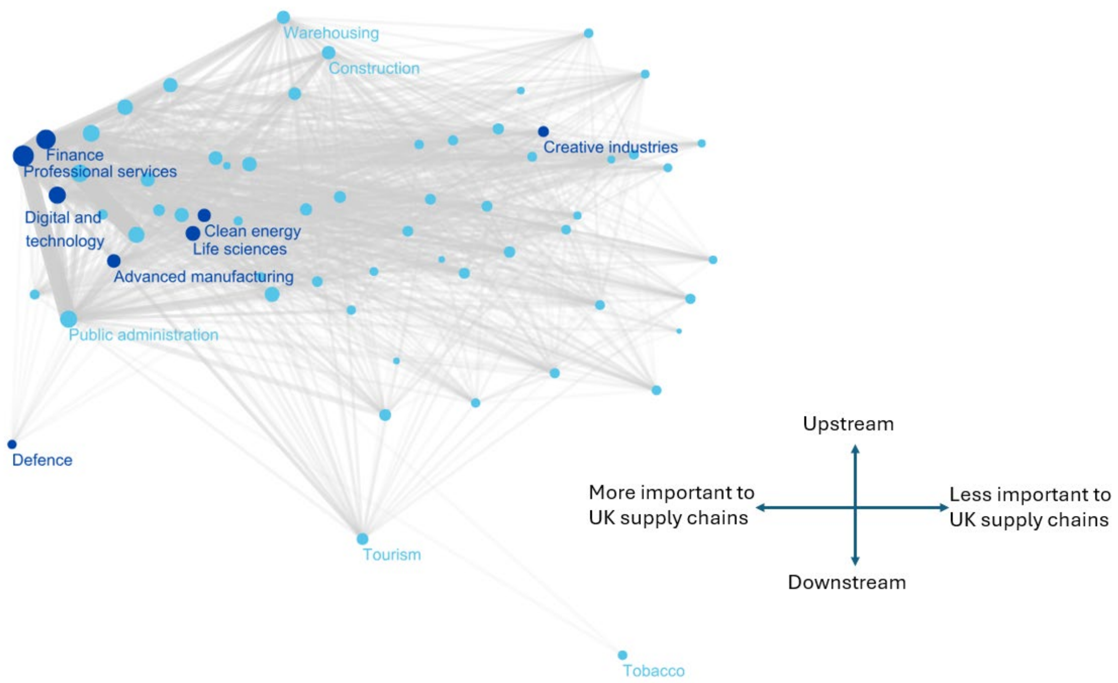
6.37 The vertical axis measures "upstreamness": the higher up an industry is in the figure, the further it is on average from the final consumer. The horizontal axis measures "network centrality": the further left an industry is in the figure, the more it is connected (directly and indirectly) to those other industries around it.

6.38 All growth-driving sectors except defence sit upstream from other industries. This means that where industries are competitive, productivity improvements are likely to propagate downstream to those other industries as input cost reductions.

6.39 Moreover, many of the growth-driving sectors are characterised by high network centrality. This means that they are directly and indirectly connected to many other industries in the economy, highlighting their importance beyond their own direct customers.

Figure 6.5: The growth-driving sectors sit at important nodes of the economic network

Centrality and upstreamness of the growth-driving sectors, UK, 2024, from ONS business-to-business payments data



Most growth-driving sectors have constant returns to scale

6.40 A second often-proposed efficiency explanation for industrial policy invokes the potential for returns to scale, scope, or learning. In other words, proponents of this theory argue that firms become more efficient the more they produce.

6.41 Whether this is true is of course an empirical question. In unpublished work, Gerarden, Reguant and Xu examine industrial policies in the clean energy sector and argue that while overall the fall in production costs validates public investment in the sector, differences in outcomes between solar and wind are due to differences in the underlying scale economies.

6.42 Whereas solar has predominantly seen improvements in materials, leading to rapidly falling costs, technological progress in wind power has taken the form of larger turbines, leading to concentrated markets and high trade costs.

6.43 Goldberg, Juhász, Lane, Lo Forte and Thurk study the global semiconductor industry. The authors document that government support, predominantly in the form of subsidies, has been important in the success of the semiconductor industry. While the authors find evidence of learning economies, they are smaller than commonly believed and come with significant cross-border knowledge spillovers.

6.44 Bessen and Tassey both provide detailed case studies of industries subject to structural change. To realise learning economies, markets and governments often need to solve complex social coordination problems and change the way economic activity is organised. This means that industrial policies may take a long time before fully filtering through to productivity.

6.45 Bartelme, Costinot, Donaldson and Rodriguez-Clare recently put this argument to the test for the aggregate US economy, using a standard general equilibrium model. While they find evidence of significant returns to scale in manufacturing sectors, the welfare gains from optimal industrial policy, under what the authors describe as optimistic assumptions, average about 1% of GDP.

6.46 Repeating a similar exercise for the UK is beyond the scope of this report. However, using methods from our recent State of Competition report, and ONS industry-level estimates of cost markups and profit shares, we can estimate returns to scale over time for the growth-driving sectors.

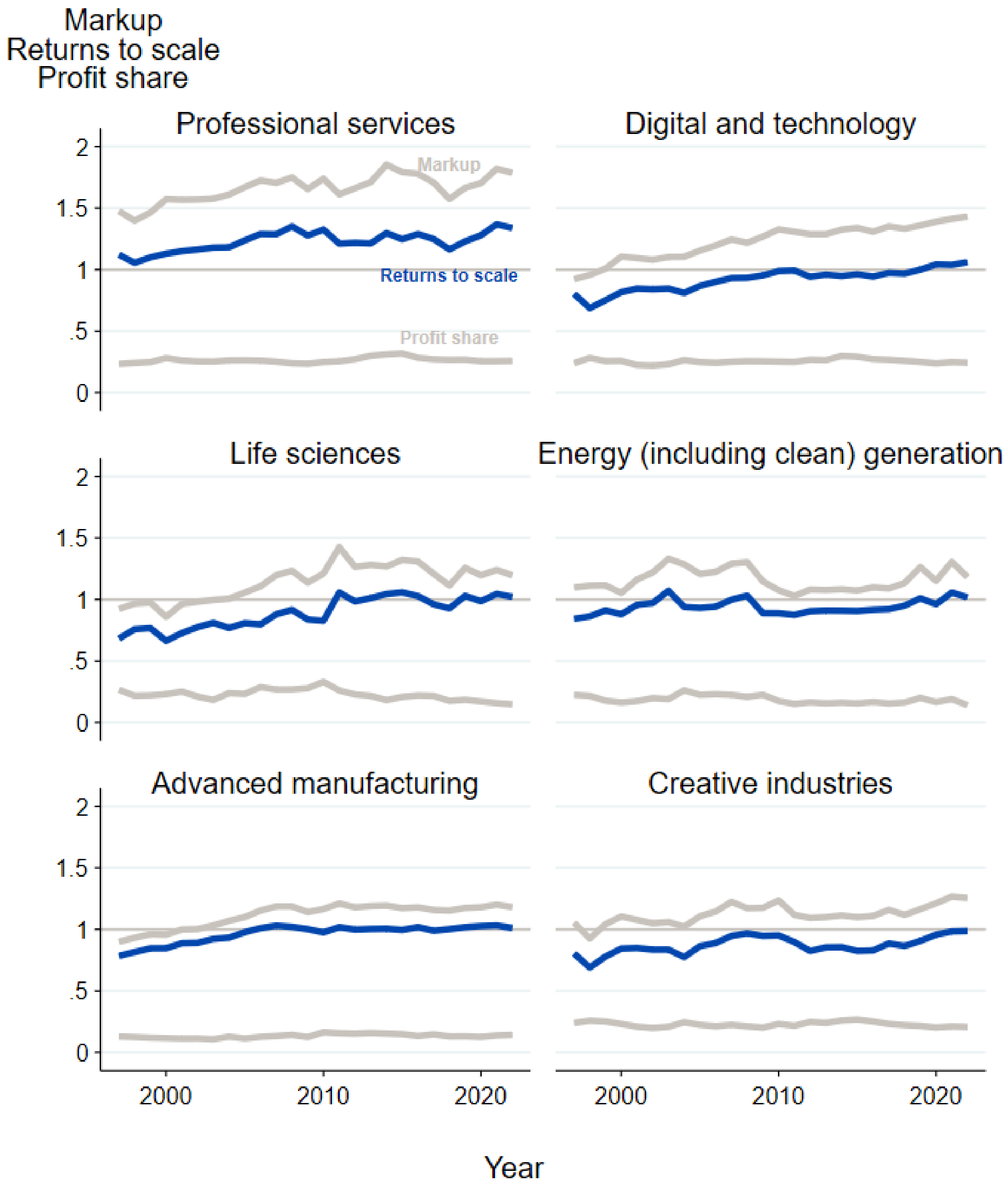
6.47 Where returns to scale are constant (that is, equal to one), increasing firm size does not yield a productivity advantage. By contrast, where returns to scale are above one, firms could potentially become more productive by growing bigger.

6.48 Figure 6.6 shows evidence of returns to scale in the UK's designated growth-driving sectors, from 1997 to 2022. We obtain these estimates by exploiting the relationship between the profit share, cost markups and returns to scale across a wide class of macroeconomic models, as argued by Kariel and Savagar.

6.49 While returns to scale have risen in many growth-driving sectors, only professional services have consistently increasing returns to scale. Of course, even within sectors with overall constant returns to scale, there may be subsectors where returns to scale are increasing.

Figure 6.6: Returns to scale may be increasing in administrative services, entertainment and wholesale and retail

Estimates of returns to scale for the growth-driving sectors, UK, 1997-2022, from ONS business microdata



Markups and profit shares at SIC 2-digit level combined to estimate the return to scale. The sectoral measures are turnover weighted averages of all the SIC 2-digit industries in the sectors of interest. For the clean energy sector, industry 27 (manufacture of electrical equipment) has been included despite only partially fitting in the sector definition, since industries 271 (manufacture of electric motors etc.) and 272 (manufacture of batteries and accumulators) constitute a non-negligible part of the industry turnover. Sources: *Office of National Statistics (ONS)*. Industries are ranked by highest returns to scale in 2021. Grey line at one for reference.

6.50 Further research in this area is needed, but these estimates suggest that productivity increases in the growth-driving sectors are unlikely to come from returns to scale, except for professional services firms.

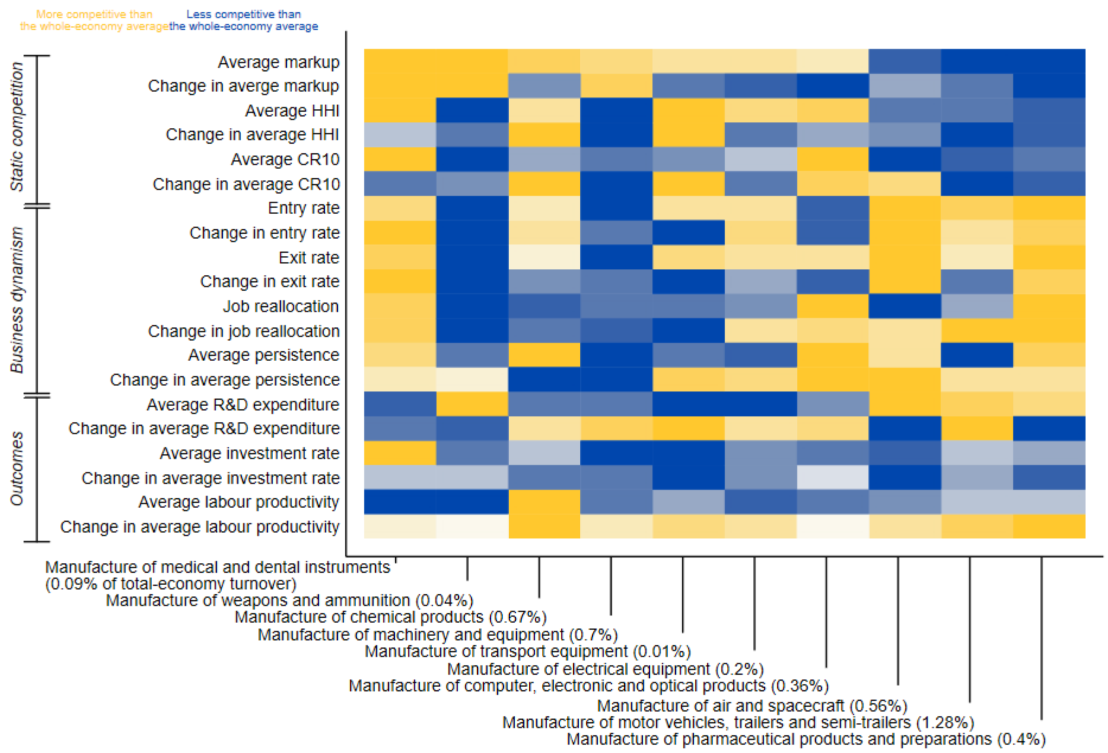
6.51 The previous sections have provided an overview of the growth-driving sectors in terms of their competitive dynamics, regional distribution, supply-chain characteristics and returns to scale. The rest of this chapter examines each of the growth-driving sectors and their component industries in turn.

Advanced manufacturing

6.52 Figure 6.7 shows how the component industries of the advanced manufacturing sector fare on static competition, business dynamism and competitive outcomes measures, relative to the whole-economy average, over the period 2005-2019.

Figure 6.7: Advanced manufacturing includes some concentrated industries

Competition measures for advanced manufacturing, UK, 2005-2019, from ONS business microdata



Each cell gives the intensity of competition (relative to the economy) in each selected measure for all the industries allocated to the 'advanced manufacturing' sector. In parenthesis the share of economy turnover c each sector. Darker shades indicate industries less competitive than the economy, yellow shades indicate industries more competitive than the economy. Darker shades reflects more extreme values. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to the period 2005-2017. Markups are calculated following our baseline approach described in the SoC report. Sectors are ranked by their average markup over that period. Sources: the *Annual Respondents Database*, (1997-2020) the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (199 2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

6.53 The heatmap shows 2019 levels and long-term (2005-2019) changes in static competition measures (such as cost markups and industry concentration), business dynamism measures (such as entry and exit rates) and outcome measures (such as innovation rates and productivity).

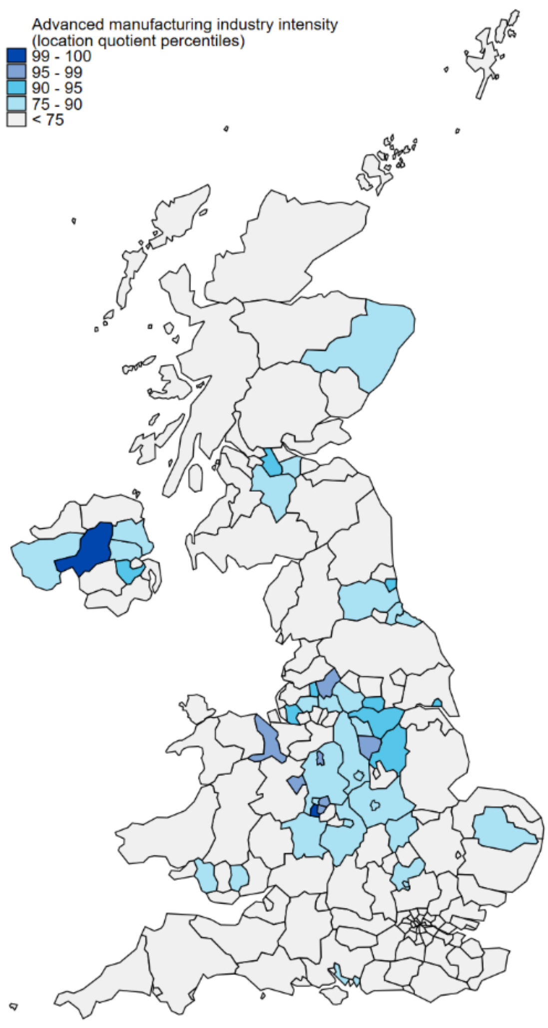
6.54 Yellow means that an industry is more competitive than the whole-economy average, while blue means it is less competitive. The more intense the shade, the more an industry differs from the rest of the economy on a particular metric.

6.55 Overall, advanced manufacturing features some heavily concentrated industries. Business dynamism across the sector is mixed. Labour productivity levels and growth rates generally exceed those in the overall economy, but investment and in some cases R&D lag behind other industries.

6.56 Figure 6.8 plots the geographical distribution of advanced manufacturing establishments across the UK. To account for differences in spatial density of economic activity, we compute establishment location quotients, which measure a region's industrial specialisation relative to the national average.

Figure 6.8: Advanced manufacturing employment is dispersed across the UK

Establishment location quotients for advanced manufacturing, UK regions, 2024, from Glass.AI data



Location quotients showing the ITL3 regions in the UK with the highest concentration of advanced manufacturing firm establishments. Source: *Glass AI* 2024.

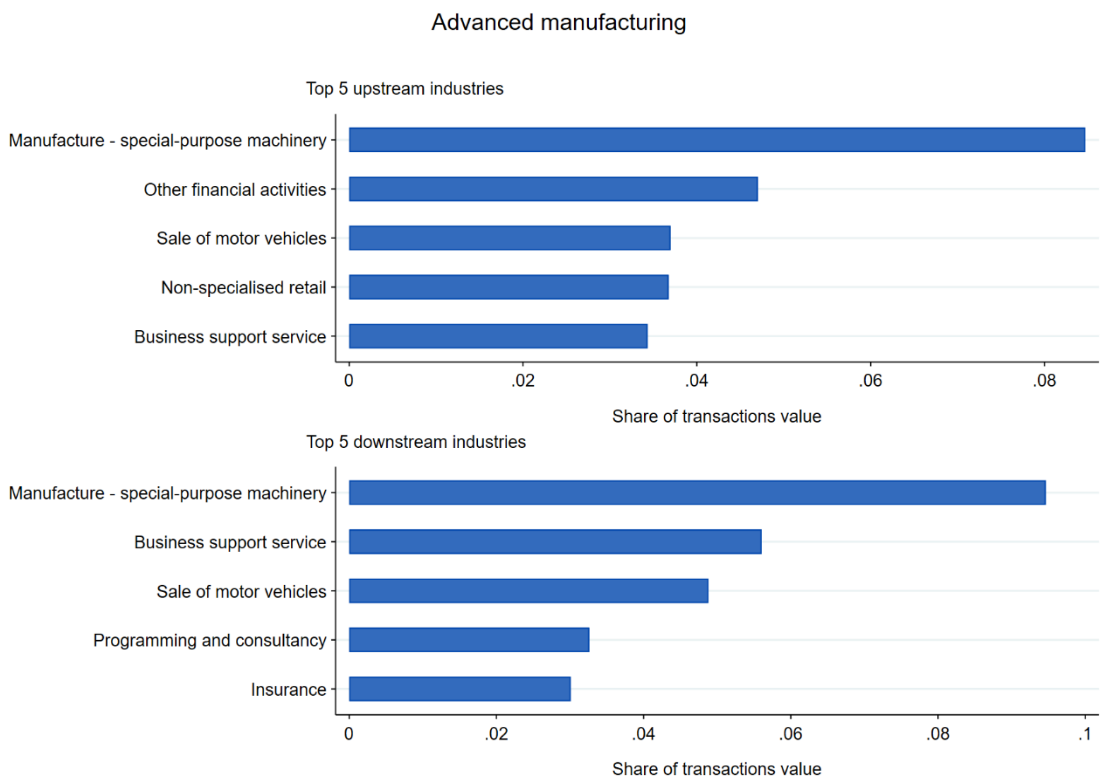
6.57 Figure 6.8 shows that advanced manufacturing is relatively dispersed across the UK. Regions that are relatively specialised in this sector (in the top quartile of the distribution of ITLS3 regions) are the Midlands, Yorkshire, Northern Ireland and parts of Scotland.

6.58 Based on existing research, like Lane's study of the South Korean manufacturing revolution, we do not expect industrial policies to only affect the sectors targeted, but also to create demand and innovation in upstream and downstream industries.

6.59 Figure 6.9 therefore shows the industries advanced manufacturing is most likely to send payments to (a proxy for purchases), and most likely to receive payments from (a proxy for sales), using the ONS' new industry-to-industry payment flows experimental data. This gives us a sense of upstream and downstream supply linkages. We exclude payments to and from public administration since they likely reflect taxes and are common to most sectors of interest (both upstream and downstream).

Figure 6.9: Advanced manufacturing closely related to machinery manufacturing

The five largest payees (upstream industries) and payers (downstream industries) for advanced manufacturing, UK, 2024, from ONS business-to-business payments data



Top 5 upstream and downstream industries for the advanced manufacturing sector in 2024. SIC industry 841 - administration of the State and the economic and social policy of the community has been excluded. Source: *Industry-to-industry payment flows* 2017-2024.

6.60 While some of these payment flows are common to many industries (including financial activities and business support services), advanced manufacturing is closely related to the manufacturing of special-purpose machinery. This suggests complementarities in productivity, but also the potential for bottlenecks.

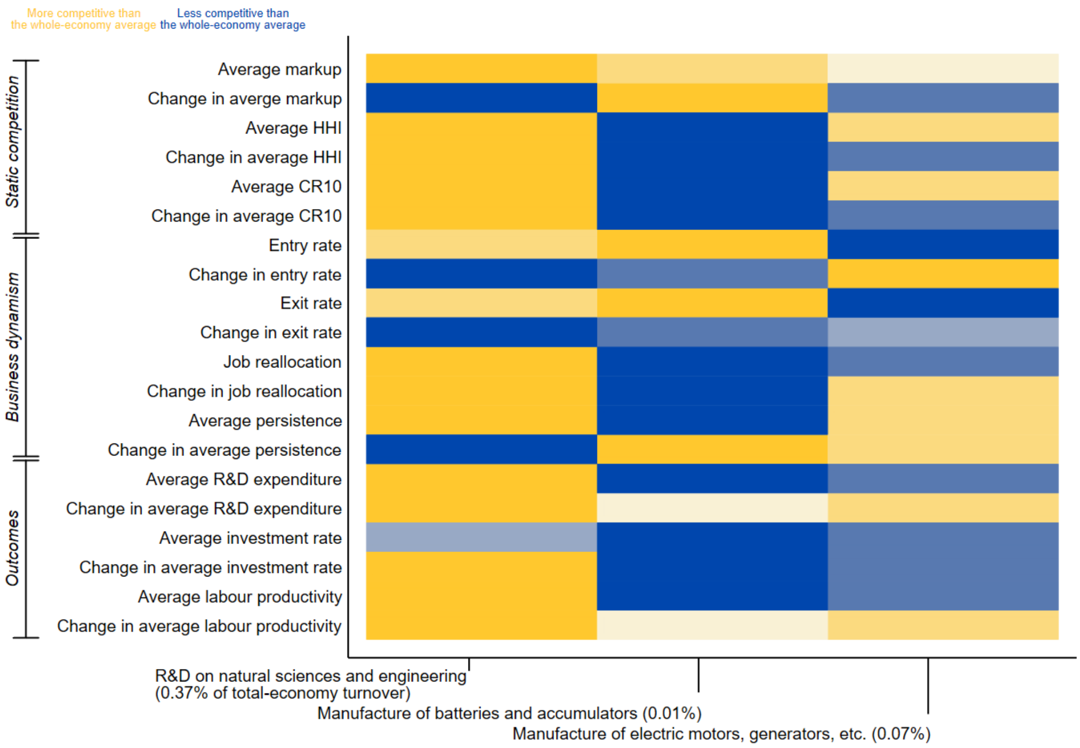
6.61 Figure E.25 in the appendix maps out the firm establishment distribution in these upstream and downstream industries across the UK. These maps can give some insight into potential geographical productivity spillover effects of the industrial strategy along industry supply chains.

Clean energy industries

6.62 Figure 6.10 shows how component industries of the clean energy industries fare on static competition, business dynamism and competitive outcomes measures, relative to the whole economy.

Figure 6.10: Clean energy industries are dynamic and competitive

Competition measures for clean energy industries, UK, 2005-2019, from ONS business microdata



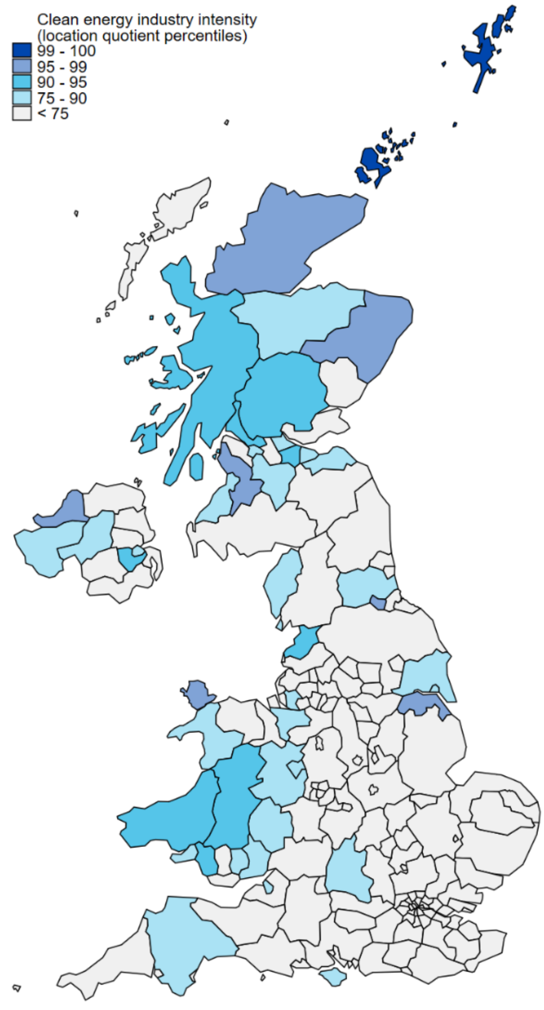
Each cell gives the intensity of competition (relative to the economy) in each selected measure for all the industries allocated to the 'clean energy' sector. In parenthesis the share of economy turnover of each sector. Darker shades indicate industries less competitive than the economy, yellow shades indicate industries more competitive than the economy. Darker shades reflects more extreme values. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to the period 2005-2017 and industry 272 - Manufacture of batteries and accumulators for which data are available only until 2016. Markups are calculated following our baseline approach described in the SoC report. Sectors are ranked by their average markup over that period. Sources: the *Annual Respondents Database* (1997-2020), the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

6.63 Clean energy is generally characterised by low market power, with R&D and productivity growing above the whole-economy trend. The services component of the sector is more dynamic, diversified, and productive than the overall economy. The manufacturing of batteries and electric vehicles is instead concentrated and lags the rest of the economy in investment.

6.64 Figure 6.11 below shows the geographical distribution of the clean energy industries. Scotland, Northern Ireland, Wales, and the West Coast of England all have significant concentrations of establishments in this sector.

Figure 6.11: Clean energy industries are located in Scotland, Northern Ireland, Wales and the South West

Establishment location quotients for clean energy industries, UK regions, 2024, from Glass.AI data

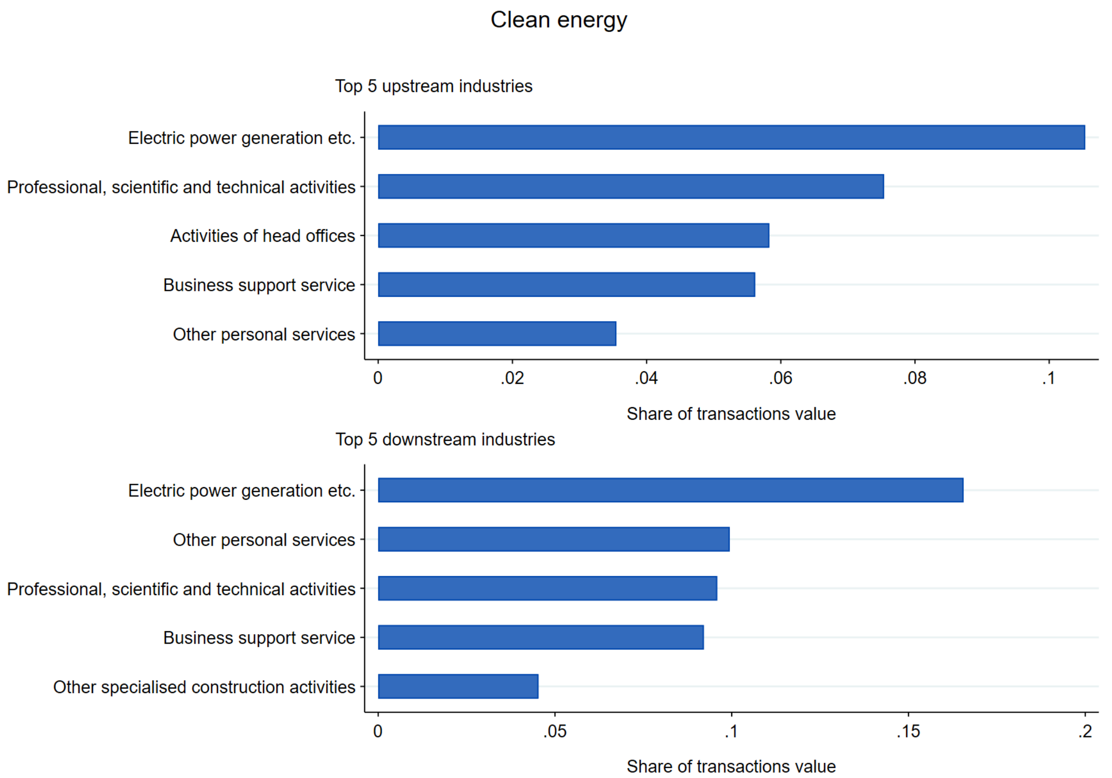


Location quotients showing the ITL3 regions in the UK with the highest concentration of clean energy industry firm establishments. Source: *Glass AI* 2024.

6.65 Figure 6.12 plots the five largest upstream and downstream industries for the clean energy sector. Of particular note are business support services and electric power generation.

Figure 6.12: Clean energy is closely linked to business support services and power generation

The five largest payees (upstream industries) and payers (downstream industries) for clean energy industries, UK, 2024, from ONS business-to-business payments data



Top 5 upstream and downstream industries for the clean energy sector in 2024. SIC industry 841 - administration of the State and the economic and social policy of the community has been excluded. Source: *Industry-to-industry payment flows* 2017-2024.

6.66 As for the other growth-driving sectors, Figure E.26 in the appendix maps out the distribution in these upstream and downstream industries across the UK.

Creative industries

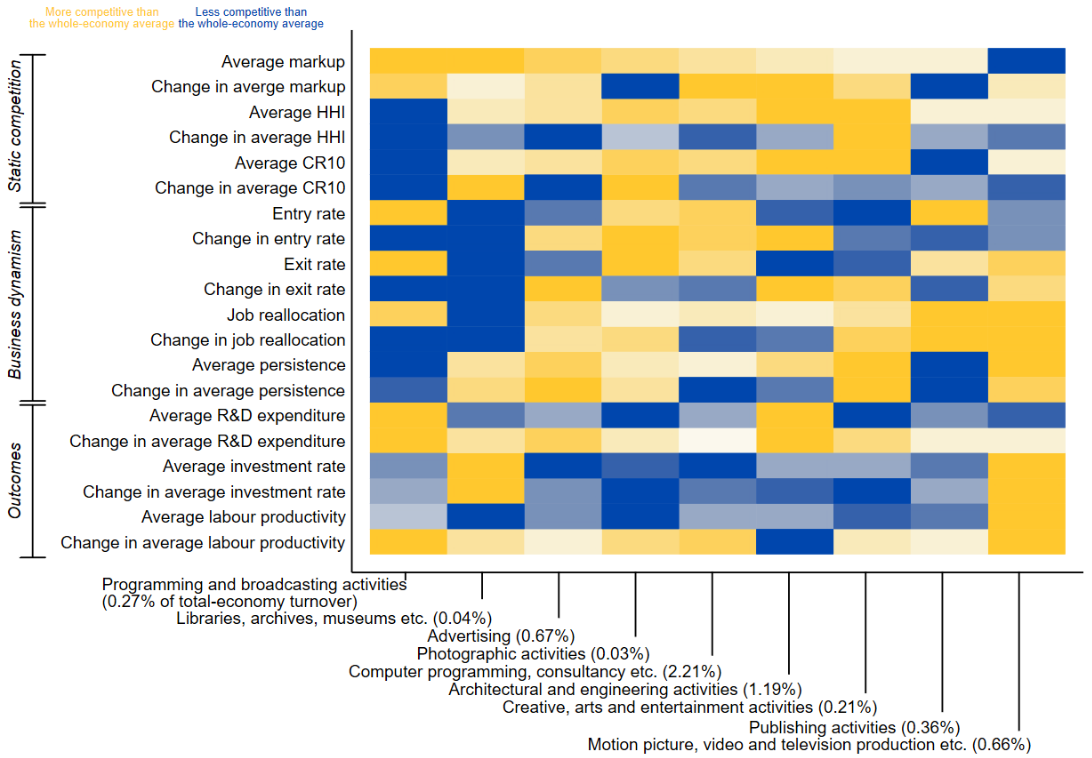
6.67 Figure 6.13 shows the same static competition, business dynamism and competitive outcomes measures for the creative industries, relative to the whole economy.

6.68 Overall, the UK creative industries are more competitive than the overall economy. R&D and productivity (except for architectural and engineering activities) are both growing above the whole-economy trend, though from below-average starting points.

6.69 Nonetheless, investment rates are generally lower and growing less than the economy-wide rates, and there are some industries of concern. For instance, programming and broadcasting is highly concentrated, with slowing entry, exit and job reallocation rates and high persistence among the largest firms at the top of the industry.

Figure 6.13: The UK creative industries are dynamic, with some exceptions

Competition measures for the creative industries, UK, 2005-2019, from ONS business microdata

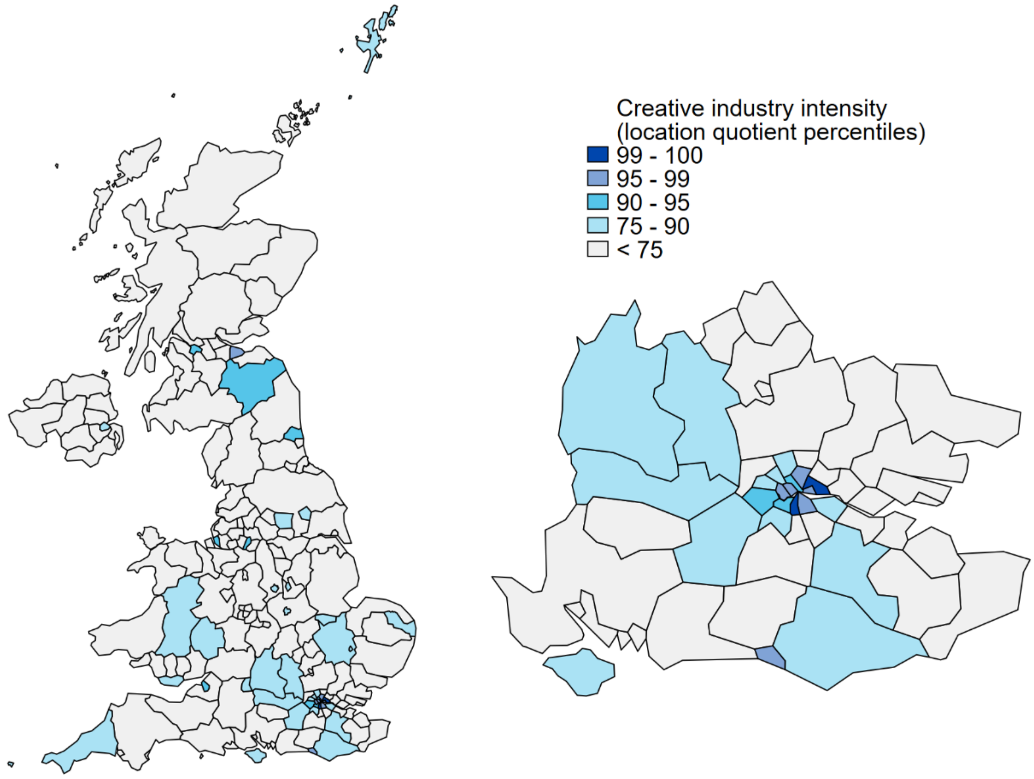


Each cell gives the intensity of competition (relative to the economy) in each selected measure for all the industries allocated to the 'creative industries' sector. In parenthesis the share of economy turnover of each sector. Darker shades indicate industries less competitive than the economy, yellow shades indicate industries more competitive than the economy. Darker shades reflects more extreme values. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to the period 2005-2017. Markups are calculated following our baseline approach described in the SoC report. Sectors are ranked by their average markup over that period. Sources: the *Annual Respondents Database*, (1997-2020) the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

6.70 Figure 6.14 plots the geographical distribution of the creative industries across the UK. The creative industries are heavily concentrated in Central London, with other pockets in Scotland, Greater Manchester, Belfast and around the country.

Figure 6.14: The creative industries are predominantly located in London

Establishment location quotients for the creative industries, UK regions, 2024, from Glass.AI data



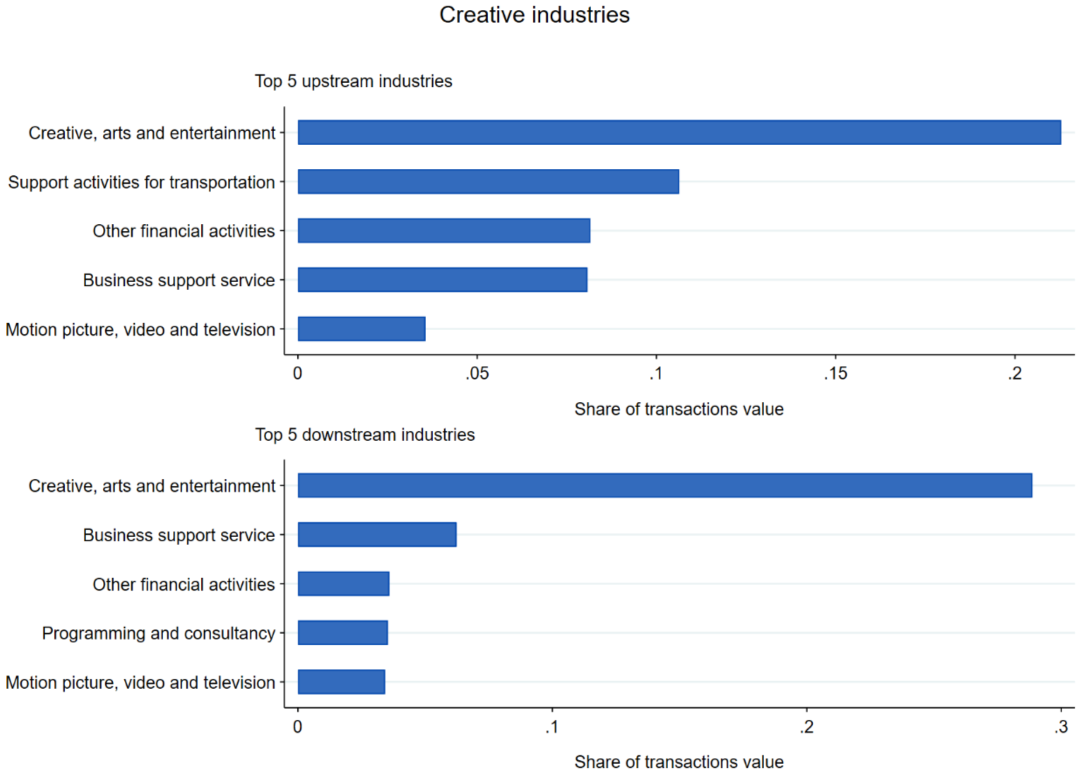
Location quotients showing the ITL3 regions in the UK and the South East of England with the highest concentration of creative industry firm establishments. Source: *Glass AI* 2024.

6.71 Figure 6.15 below shows that the creative industries have tight input-output linkages with business support and creative, arts and entertainment activities, while programming and consultancy industries are an important downstream link.

6.72 Figure E.27 in the appendix maps out the locations of these upstream and downstream industries across the UK.

Figure 6.15: The creative industries are tightly linked to business support and programming and consultancy

The five largest payees (upstream industries) and payers (downstream industries) for the creative industries, UK, 2024, from ONS business-to-business payments data



Top 5 upstream and downstream industries for the creative industries sector in 2024. SIC industry 841 - administration of the State and the economic and social policy of the community has been excluded. Source: *Industry-to-industry payment flows* 2017-2024.

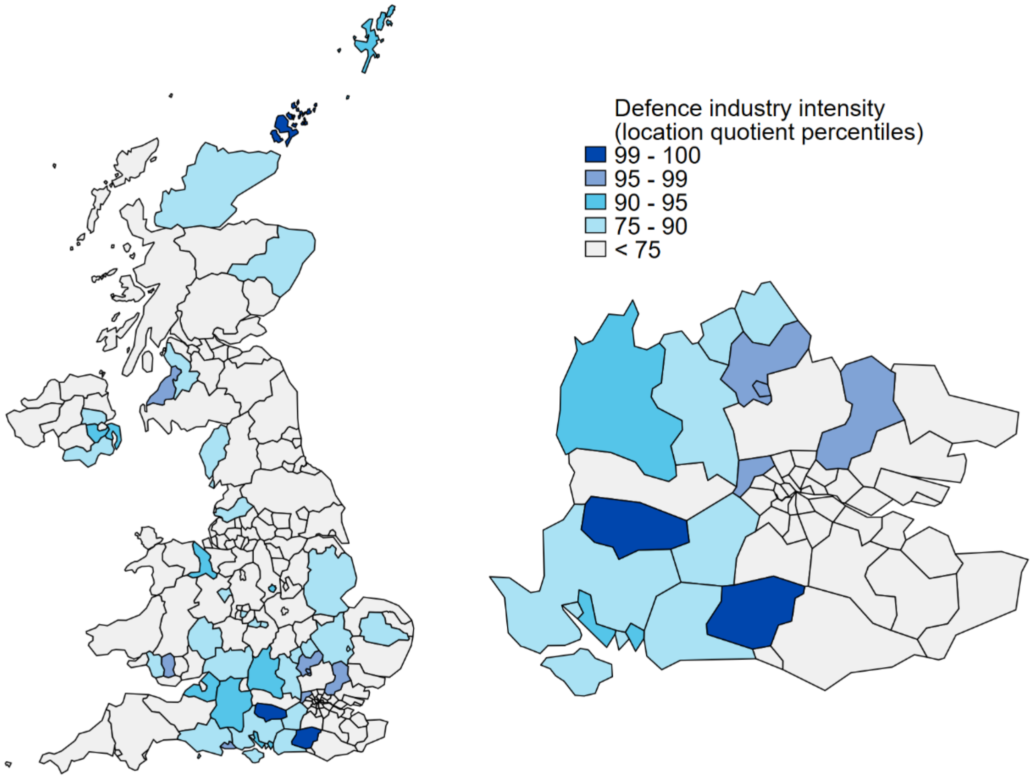
Defence

6.73 The defence sector, alongside financial services, is one of the two key growth sectors where issues with measuring inputs and outputs render our standard competition measures misleading. We therefore omit our standard heatmap here.

6.74 Figure 6.16 shows the geographical distribution of the defence industries. Defence establishments are spread throughout the South, including West London, parts of the Midlands and the North West, and parts of Scotland and Northern Ireland.

Figure 6.16: Defence industries are mostly located in the central parts of the south of the UK

Establishment location quotients for the defence industries, UK regions, 2024, from Glass.AI data



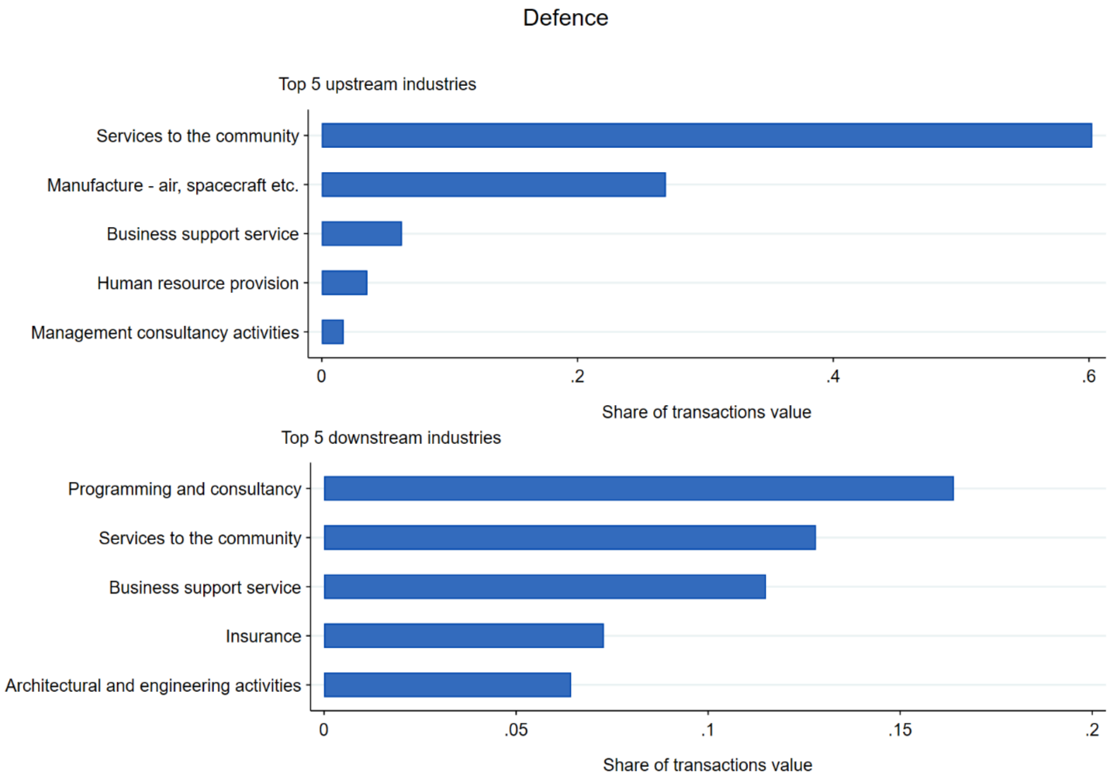
Location quotients showing the ITL3 regions in the UK and the South East of England with the highest concentration of defence Industry firm establishments. Source: *Glass AI* 2024.

6.75 Figure 6.17 shows the industries with the largest upstream and downstream transaction links to the defence industries. These are community services, and business support services. An important upstream link is the manufacture of air and spacecraft and related machinery.

6.76 Figure E.28 in the appendix shows the geographical distribution of these industries across the UK.

Figure 6.17: Defence manufacturing is linked to community services and other manufacturing

The five largest payees (upstream industries) and payers (downstream industries) for defence manufacturing, UK, 2024, from ONS business-to-business payments data



Top 5 upstream and downstream industries for the defence sector in 2024. SIC industry 841 - administration of the State and the economic and social policy of the community has been excluded. Source: *Industry-to-industry payment flows* 2017-2024.

Digital and technologies

6.77 Classifying firms using the Standard Industrial Classification (SIC) may be particularly problematic in the digital and technologies sector. Many markets in this sector have emerged since the last SIC reform in 2007, making it difficult for firms to correctly self-classify. We explore the implications of this measurement issue in Chapter 8.

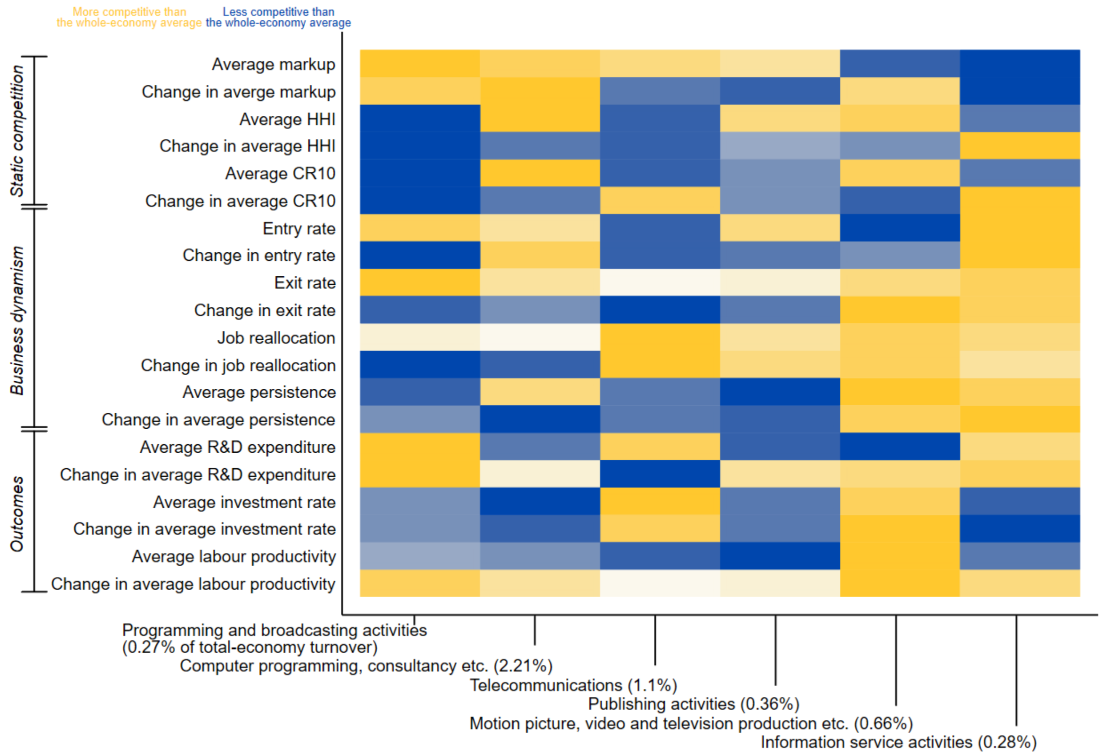
6.78 Figure 6.18 compares the likely component industries of the digital and technologies key sector to the rest of the economy.

6.79 Within the digital and technologies sector, there is wide variation in competitive behaviour and outcomes. For instance, programming and broadcasting activities are a heavily concentrated industry, with little in the way of business dynamism. Entry and exit rates are low, and the persistence of the largest firms at the top is high. While firms invest little in this industry, labour productivity is nonetheless growing above the whole-economy trend even if starting from a lower level.

6.80 Information services activities on the other hand appears to be a very dynamic industry, performing better than the overall economy on all the business dynamism indicators. However, it has high (and growing above the whole-economy trend) markups, high (but improving) concentration and low investment rates.

Figure 6.18: Competitive dynamics vary across the digital and technologies industries

Competition measures for digital and technologies, UK, 2005-2019, from ONS business microdata

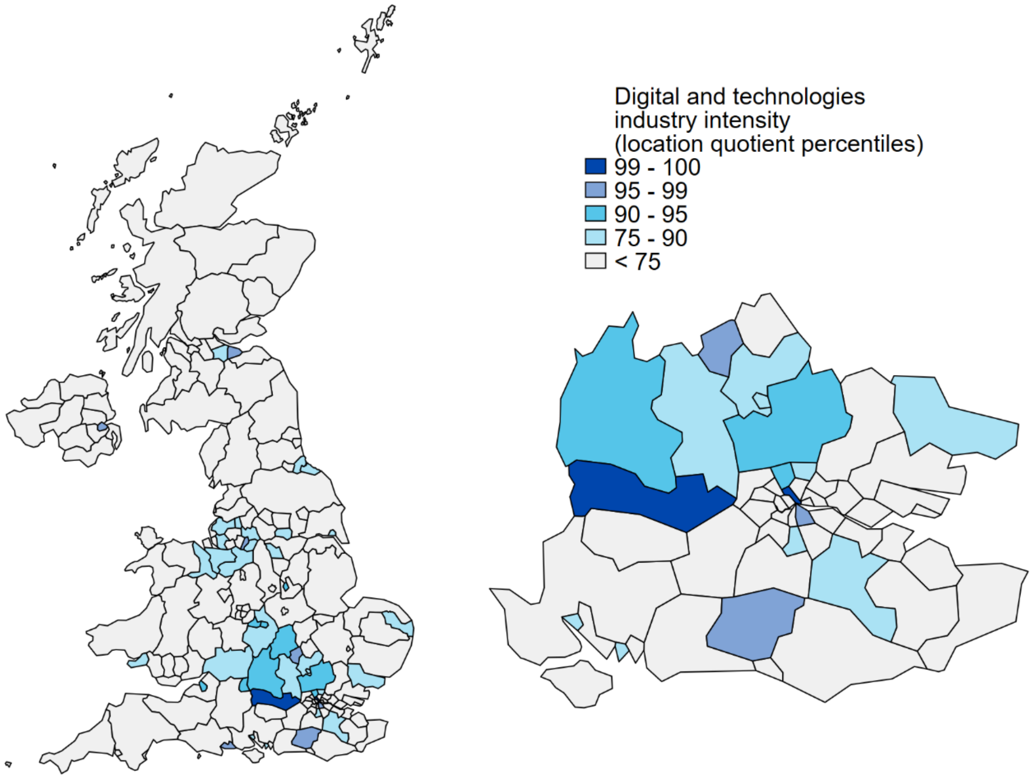


Each cell gives the intensity of competition (relative to the economy) in each selected measure for all the industries allocated to the 'digital and technology' sector. In parenthesis the share of economy turnover of each sector. Darker shades indicate industries less competitive than the economy, yellow shades indicate industries more competitive than the economy. Darker shades reflects more extreme values. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to the period 2005-2017. Markups are calculated following our baseline approach described in the SoC report. Sectors are ranked by their average markup over that period. Sources: the *Annual Respondents Database*, (1997-2020) the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

6.81 Figure 6.19 shows the geographic distribution of employment within digital and technology industries. Digital and technologies industries are almost exclusively concentrated in the South East, with London, Berkshire and Oxfordshire particularly well represented and Cambridgeshire and Bristol also in the top quarter of the distribution.

Figure 6.19: Digital and technologies industries are mostly concentrated in the South East

Establishment location quotients for the growth-driving sectors, UK regions, 2024, from Glass.AI data



Location quotients showing the ITL3 regions in the UK and the South East of England with the highest concentration of digital and technologies firm establishments. Source: *Glass AI* 2024.

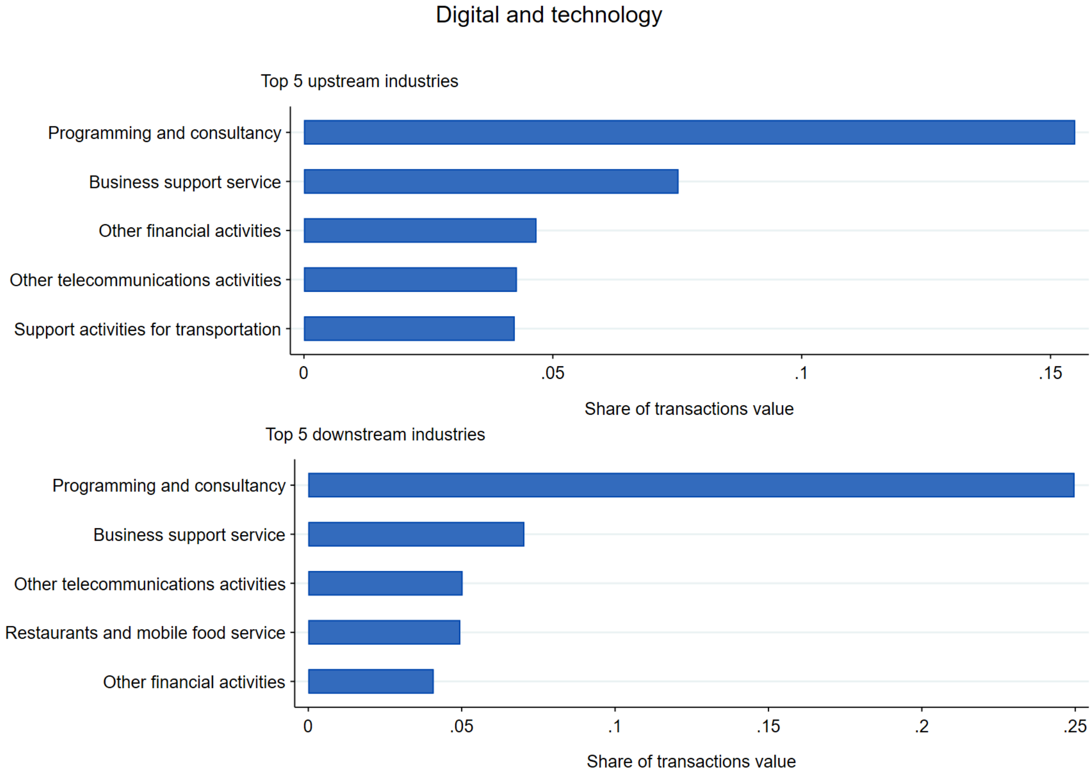
6.82 Figure 6.20 plots the top five upstream and downstream industries for the digital and technologies sector.

6.83 Many of the same industries are linked both upstream and downstream, including programming and consultancy, business support, telecommunication, and financial activities. Some of these industries are themselves part of other growth-driving sectors, such as financial services and professional and business services.

6.84 The geographical distribution of these industries across the UK can be found Figure E.29 in the appendix.

Figure 6.20: Digital and technologies mostly supplies, and is supplied by, professional and digital services

The five largest payees (upstream industries) and payers (downstream industries) for digital and technologies, UK, 2024, from ONS business-to-business payments data



Top 5 upstream and downstream industries for the digital and technology sector in 2024. SIC industry 841 - administration of the State and the economic and social policy of the community has been excluded. Source: *Industry-to-industry payment flows* 2017-2024.

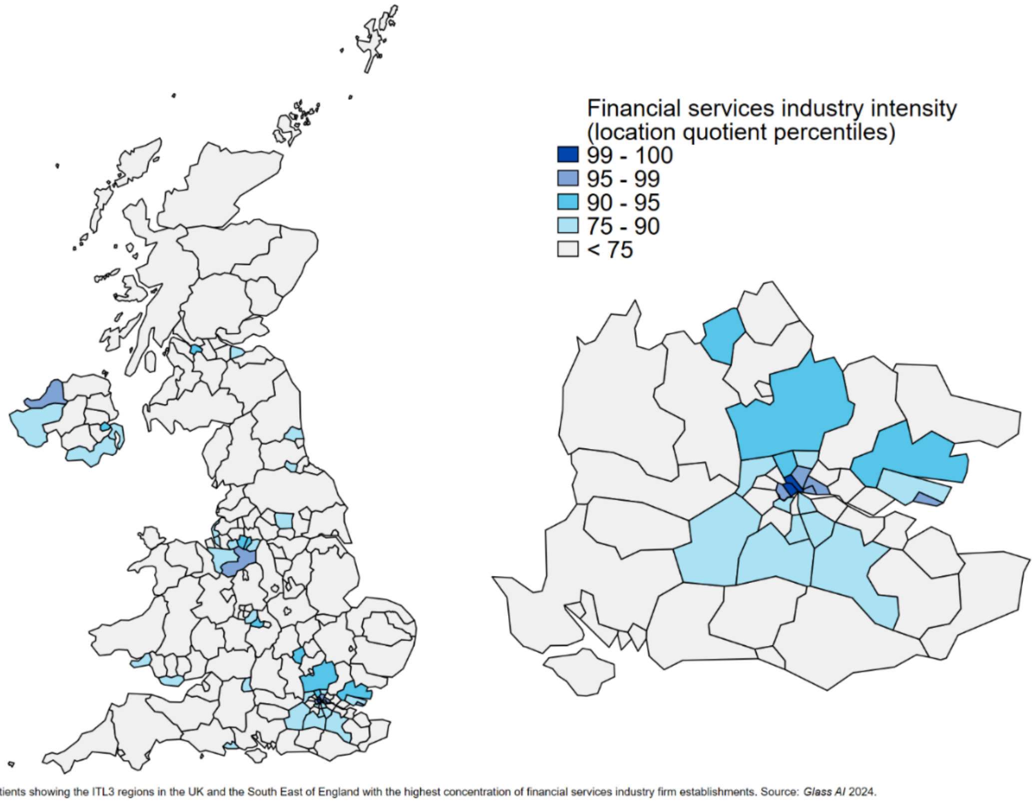
Financial services

6.85 Financial services, alongside the defence sector, has measurement issues in inputs and outputs that mean we do not present our usual competition heatmap.

6.86 Figure 6.21 shows the distribution of financial services across the UK. Central and Greater London both show substantial industry presence, but so do other urban centres across the country, including Belfast, Cardiff, Birmingham, Edinburgh, and Leeds.

Figure 6.21: Financial services are concentrated in urban centres around the country, particularly Greater London

Establishment location quotients for financial services, UK regions, 2024, from Glass.AI data

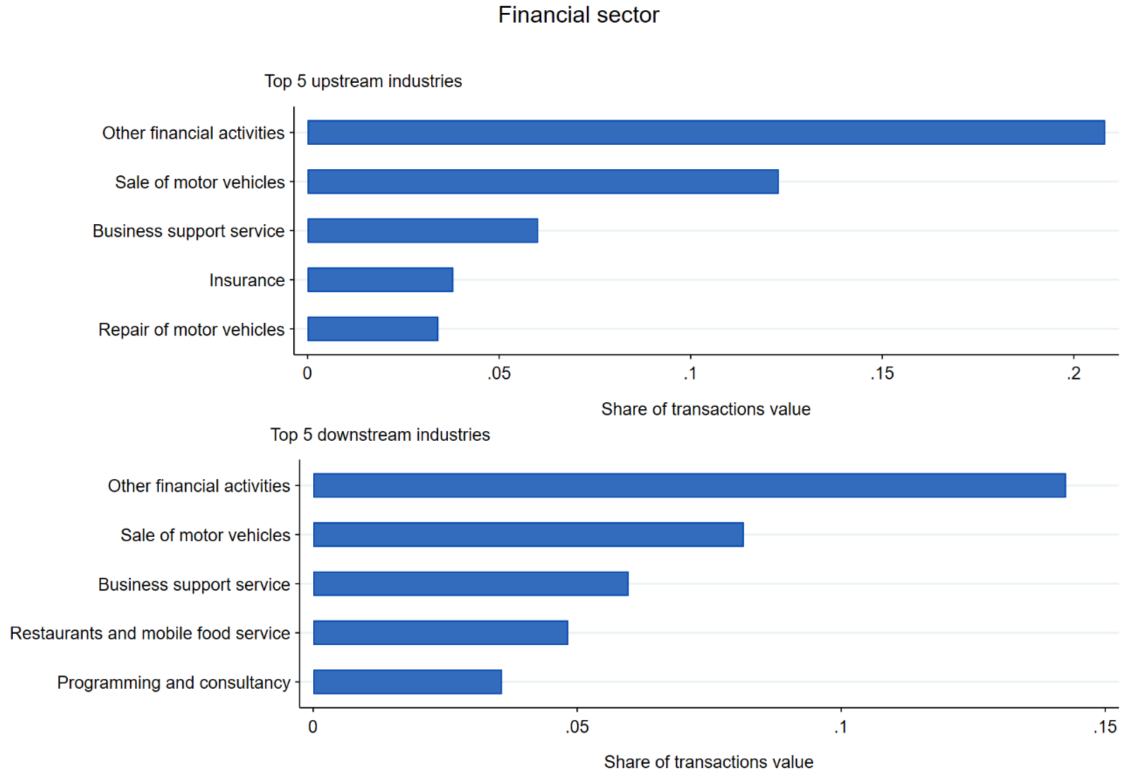


6.87 Figure 6.22 below shows the closest upstream and downstream industries for financial services. These are linked to other financial services, motor vehicle financing, business support and insurance services.

6.88 Figure E.30 in the appendix shows the distribution of upstream and downstream industries for the financial sector across the UK.

Figure 6.22: Financial services are linked to other financial activities, car financing and business support

The five largest payees (upstream industries) and payers (downstream industries) for the financial services, UK, 2024, from ONS business-to-business payments data



Top 5 upstream and downstream industries for the financial services sector in 2024. SIC industry 841 - administration of the State and the economic and social policy of the community has been excluded. Source: *Industry-to-industry payment flows* 2017-2024.

Life sciences

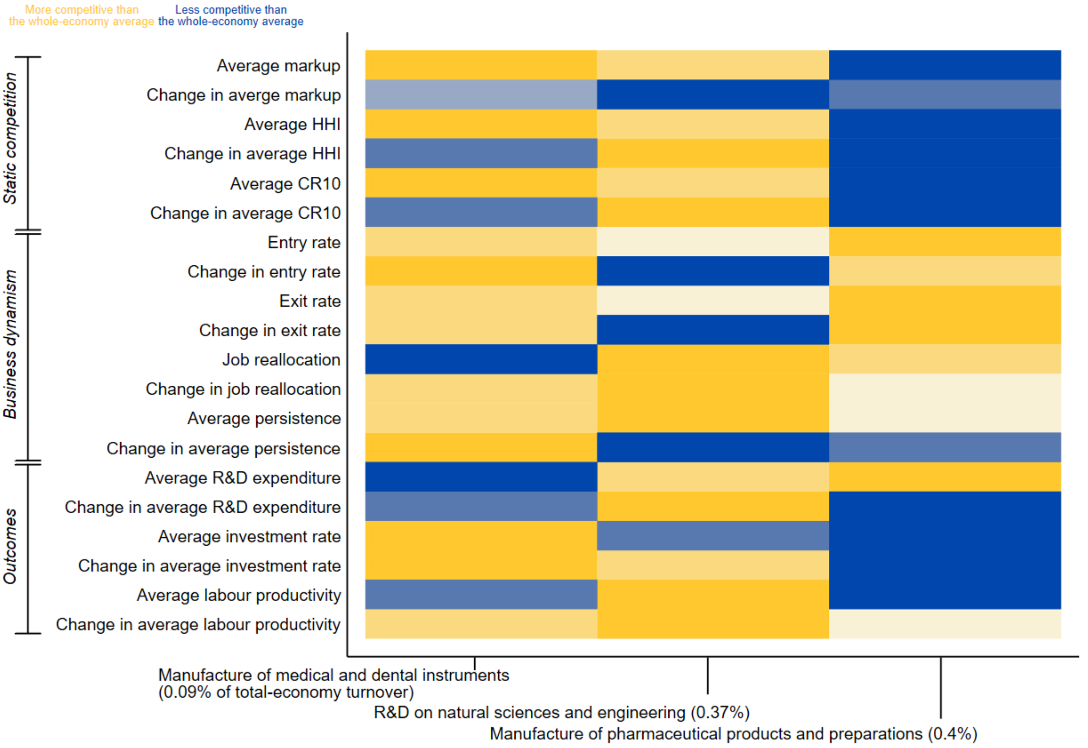
6.89 Figure 6.23 shows how component industries of the life sciences sector fare on static competition, business dynamism and competitive outcomes measures, relative to the whole economy.

6.90 The life sciences are generally quite dynamic and competitive, with high entry, exit and job reallocation rates, and generally low markups. Investment is also generally high and growing above the whole-economy trend.

6.91 The one exception is the manufacture of pharmaceuticals, which has high markups and concentration, both growing above the whole-economy trend, and low investment. This suggests policymakers may want to better understand competitive dynamics in this industry.

Figure 6.23: The life sciences are dynamic, and with one exception competitive and highly productive

Competition measures for the life sciences, UK, 2005-2019, from ONS business microdata

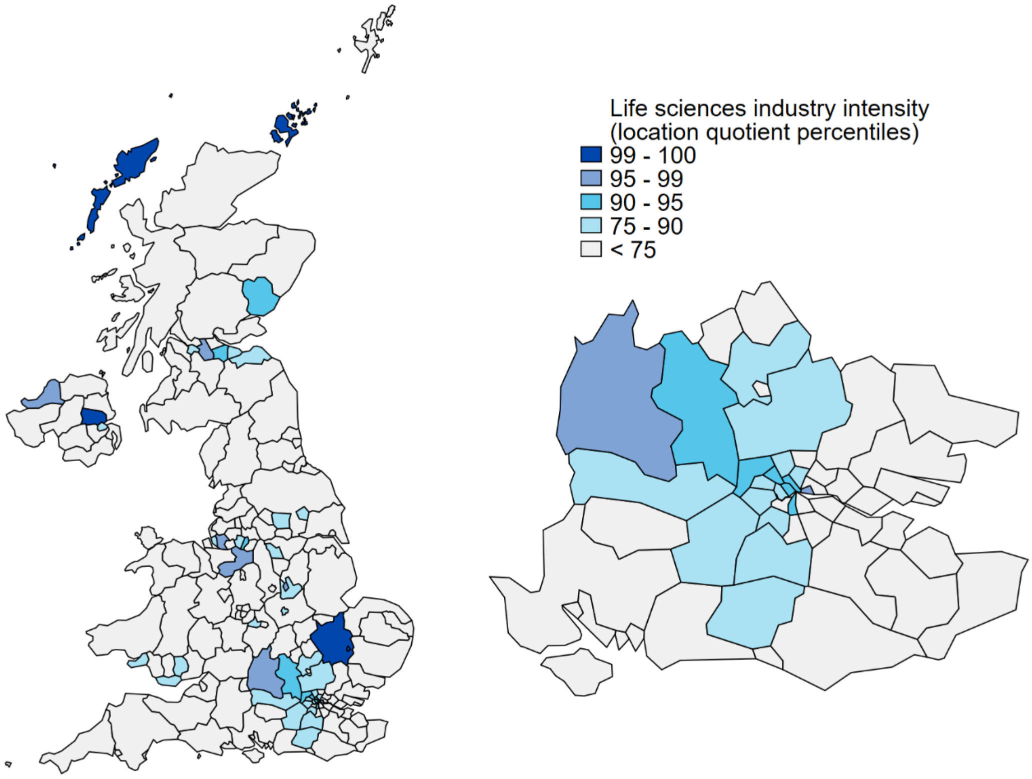


Each cell gives the intensity of competition (relative to the economy) in each selected measure for all the industries allocated to the 'life sciences' sector. In parenthesis the share of economy turnover of each sector. Darker shades indicate industries less competitive than the economy, yellow shades indicate industries more competitive than the economy. Darker shades reflects more extreme values. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to the period 2005-2017. Markups are calculated following our baseline approach described in the SoC report. Sectors are ranked by their average markup over that period. Sources: the *Annual Respondents Database*, (1997-2020) the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

6.92 Figure 6.24 shows the geographical distribution of the life sciences across the UK. Life science establishments are particularly concentrated in London, the Oxford-Cambridge arc, Scotland and the North West of England.

Figure 6.24: Life sciences are present in London, the Oxford-Cambridge arc, Scotland and the North West

Establishment location quotients for the growth-driving sectors, UK regions, 2024, from Glass.AI data



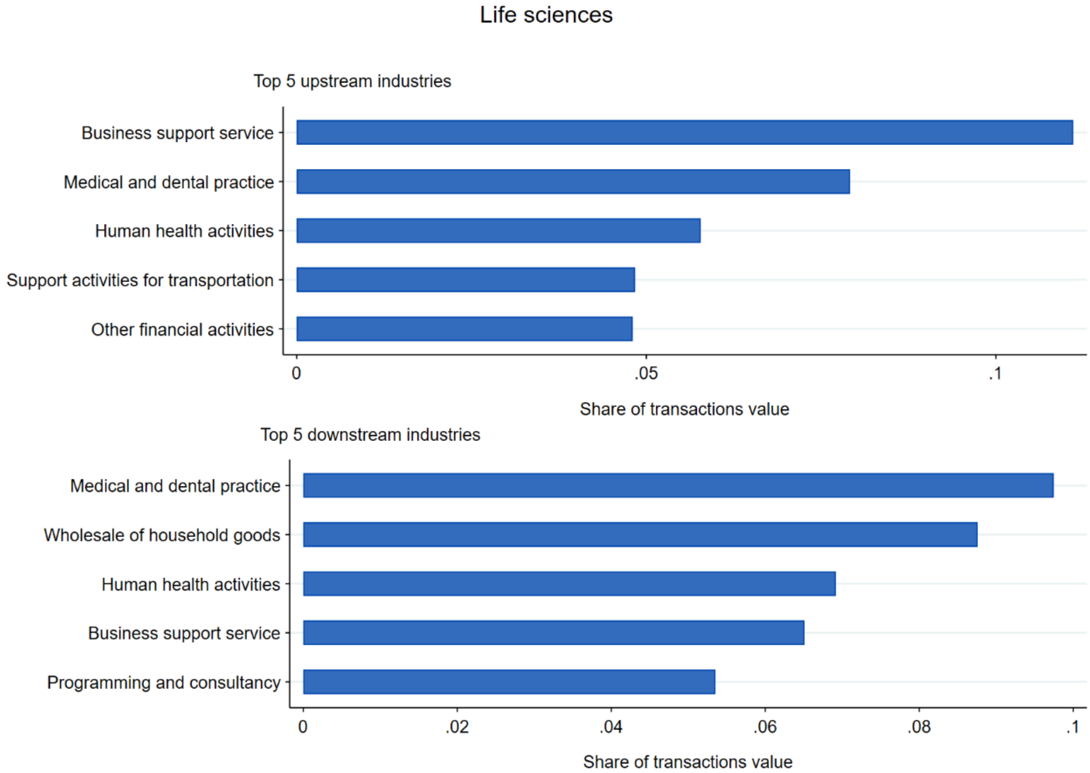
Location quotients showing the ITL3 regions in the UK and the South East of England with the highest concentration of life sciences industry firm establishments. Source: *Glass AI* 2024.

6.93 Figure 6.25 below shows the upstream and downstream payment linkages of firms in the life sciences. The life sciences are predominantly linked to business support, human health activities and medical and dental practices.

6.94 Figure E.31 in the appendix once again shows the distribution of these industries across the regions and nations of the UK.

Figure 6.25: The life sciences are linked to business support, human health activities and medical and dental practices

The five largest payees (upstream industries) and payers (downstream industries) for the life sciences, UK, 2024, from ONS business-to-business payments data



Top 5 upstream and downstream industries for the life sciences sector in 2024. SIC industry 841 - administration of the State and the economic and social policy of the community has been excluded. Source: *Industry-to-industry payment flows* 2017-2024.

Professional and business services

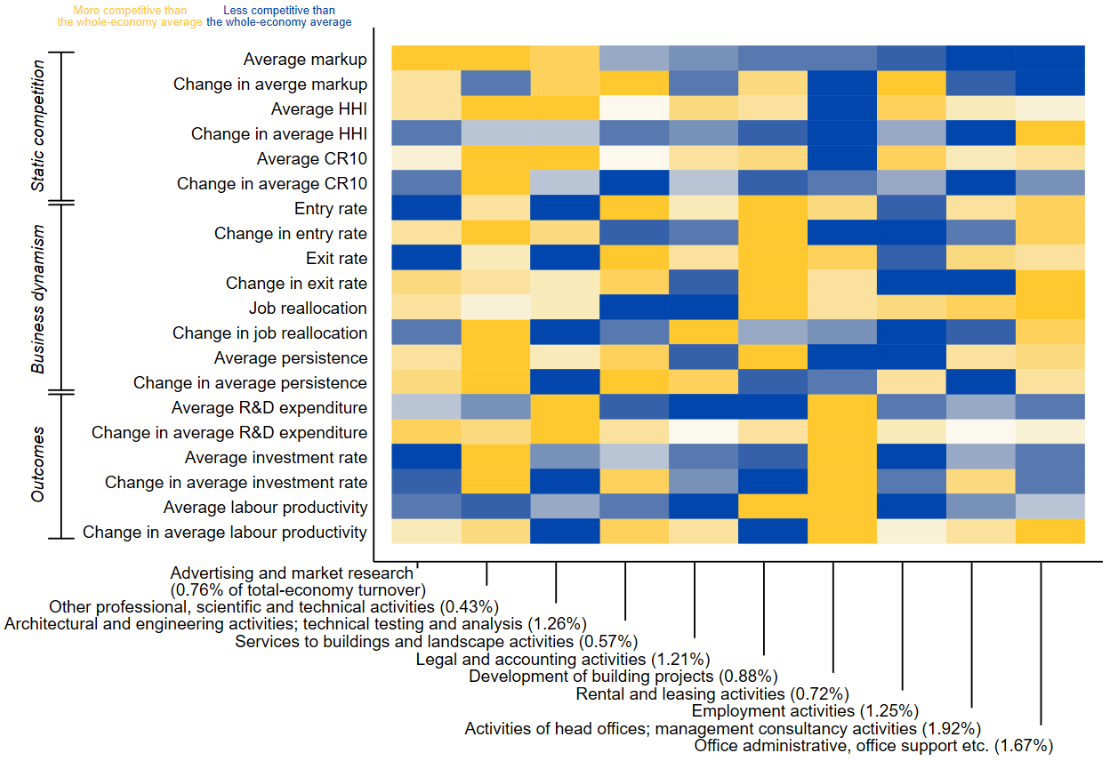
6.95 Figure 6.26 shows how component industries of the professional services sector fare on static competition, business dynamism and competitive outcomes measures, relative to the whole economy.

6.96 Professional and business services make up one of the largest key sectors, with a correspondingly mixed picture. Some component industries, such as other professional, scientific and technical activities are highly competitive, dynamic with dispersed market shares. Others, like rental and leasing activities are productive, innovative and invest more than the whole-economy average, but are also characterised by high markups, concentration, and persistence at the top.

6.97 This variation suggests policymakers will want to tailor and monitor industrial policies carefully in this sector to make sure they reach those firms most likely to spur wider productivity growth.

Figure 6.26: Professional services span a broad range of more and less competitive industries

Competition measures for professional services, UK, 2005-2019, from ONS business microdata

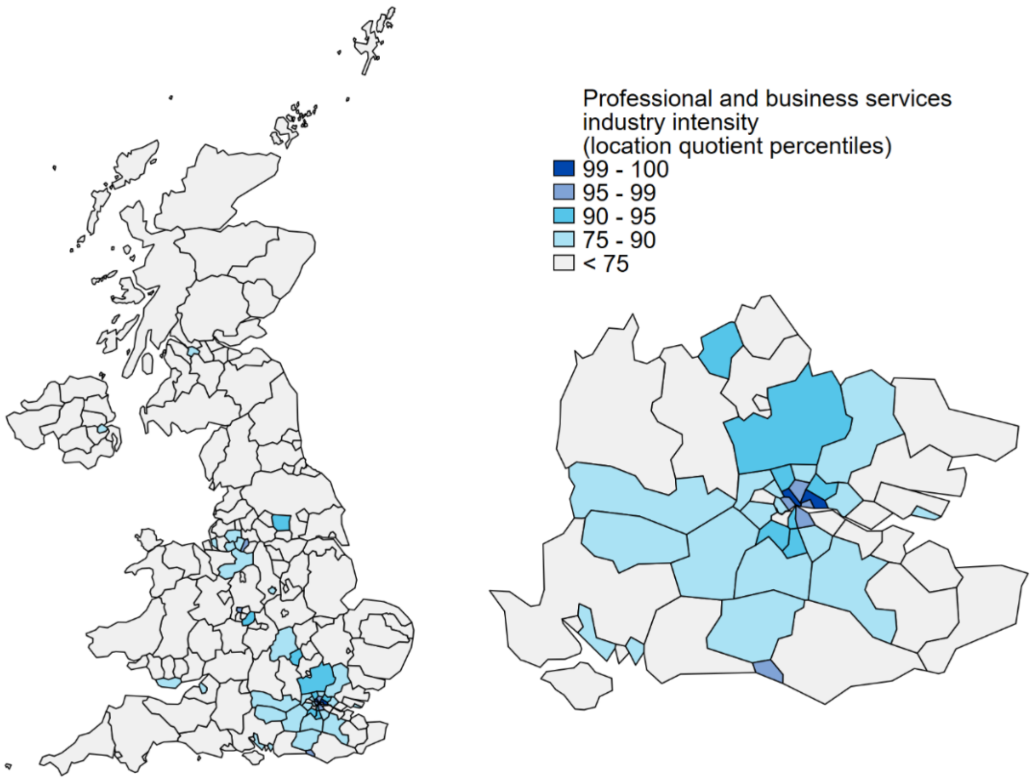


Each cell gives the intensity of competition (relative to the economy) in each selected measure for all the industries allocated to the 'professional and business services' sector. In parenthesis the share of economy turnover of each sector. Darker shades indicate industries less competitive than the economy, yellow shades indicate industries more competitive than the economy. Darker shades reflects more extreme values. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to the period 2005-2017. Markups are calculated following our baseline approach described in the SoC report. Sectors are ranked by their average markup over that period. Sources: the *Annual Respondents Database*, (1997-2020) the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

6.98 Figure 6.27 plots the geographical concentration of professional service establishments. Most of them are located in the South East, with Central London particularly heavily represented. Other pockets of concentration exist in Scotland, around Bristol and Greater Manchester.

Figure 6.27: Professional services are concentrated mainly in London and the South East

Establishment location quotients for professional services, UK regions, 2024, from Glass.AI data



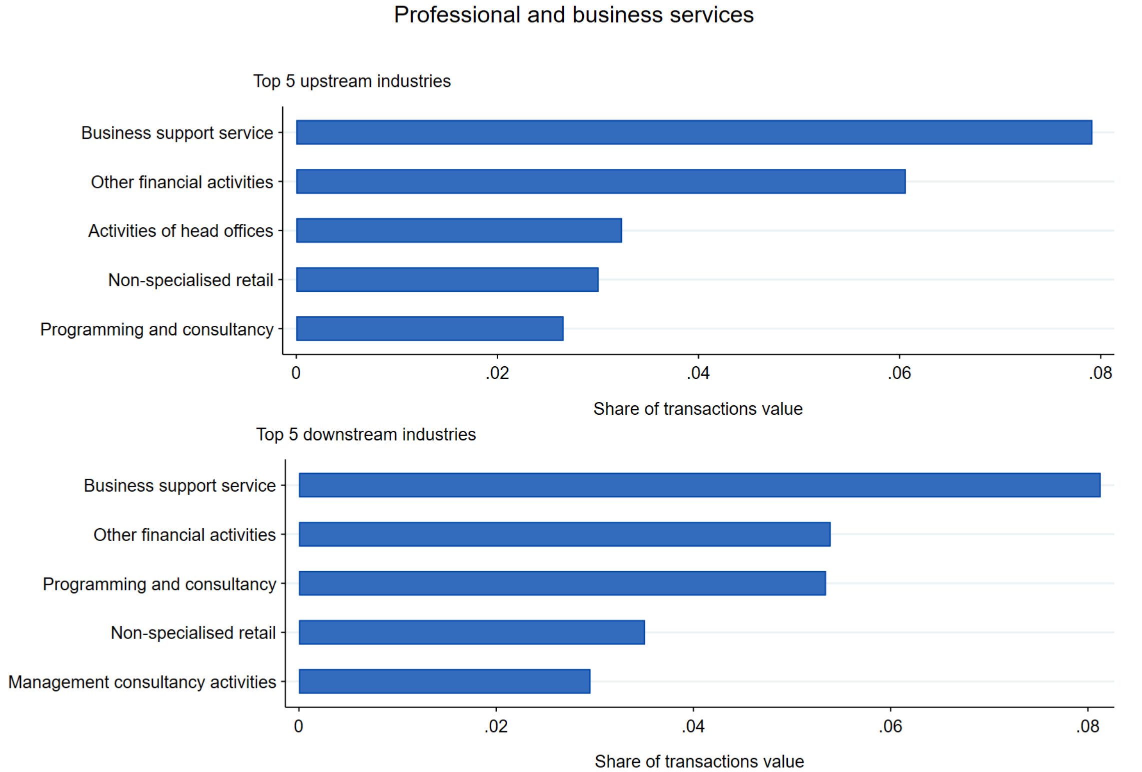
Location quotients showing the ITL3 regions in the UK and the South East of England with the highest concentration of professional and business services industry firm establishments. Source: *Glass AI* 2024.

6.99 Figure 6.28 examines the most common upstream and downstream industries for firms in the professional services sector. Professional services firms are connected to business support, financial services and programming and consultancy.

6.100 Finally, Figure E.32 in the appendix maps out the relevant upstream and downstream industries across the UK.

Figure 6.28: Professional services are most closely linked with business support services and financial services

The five largest payees (upstream industries) and payers (downstream industries) for professional services, UK, 2024, from ONS business-to-business payments data



Top 5 upstream and downstream industries for the professional and business services sector in 2024. SIC industry 841 - administration of the State and the economic and social policy of the community has been excluded.
Source: *Industry-to-industry payment flows* 2017-2024.

6.101 This chapter has summarised competition and productivity indicators for the industries comprising the growth-driving sectors, their regional and supply-chain footprint and presented evidence of sector-level returns to scale.

6.102 Together, these diagnostics can help the UK government and the public understand the likely impacts of, and bottlenecks for, an industrial strategy.

6.103 For many countries, specific and consistent published evidence on their growth-driving sectors is still sparse. An exception is France Stratégie, which recently surveyed the causes of French deindustrialisation, and comparative strengths and weaknesses of seven key industrial sectors.

6.104 The next chapter places this evidence in the wider context of the other pillars of the growth mission. It provides some sense of the importance of industrial strategy within the wider growth mission, and the possible bottlenecks arising from shortcomings in other policy areas.

7. What do the other growth pillars mean for industrial policy?

7.1 The UK government's industrial strategy and trade strategy together form one of the seven pillars of the wider growth mission. They sit alongside policies on investment, people, stability, place, innovation, and Net Zero.

7.2 There are two reasons understanding the UK's comparative performance on these other growth pillars matters for the UK's industrial strategy. First, most policies have financial costs.

7.3 Knowledge of relative priorities enables a better discussion of the trade-offs involved in different policy choices. For instance, if the UK lags much behind peer countries in investment or skills, government may prefer to prioritise spending in these areas over others.

7.4 Second, where growth pillars cover aspects of the growth-driving sectors, the UK's sector-specific relative performance may directly impact the effectiveness of the chosen industrial strategy.

7.5 For instance, the UK's shortage in engineering and computer programming skills may create bottlenecks for businesses in advanced manufacturing and digital and technologies, potentially reducing the effectiveness of any vertical policies directed at those sectors.

7.6 Criscuolo, Gonne, Kitazawa and Lalanne in their review of the available evidence also stress the crucial role that horizontal skills, technology and competition policies play in enabling vertical industrial policies.

7.7 Many UK policy research institutions have examined the UK's comparative performance on some of the growth pillars, including skills, regional inequality, Net Zero and trade. This chapter instead brings together high-level evidence on all growth pillars, and how they relate to the industrial strategy. In doing so, it barely scratches the surface and highlights the need for more research.

7.8 We find key shortfalls in investment, innovation, and skills, compared to peer nations. These findings come with caveats, however: for instance, once a wider set of intangibles is accounted for, the UK's investment performance looks better than in national accounts estimates. This reflects the UK's strengths in services and in the digital sector.

7.9 For investment and skills, we provide further evidence at the growth-driving sector level. We find that even in these sectors, the UK underinvests compared to its international peers. Skills may present a bottleneck in some growth-driving sectors, like life sciences and advanced manufacturing.

Investment, innovation, and skills are areas for UK improvement

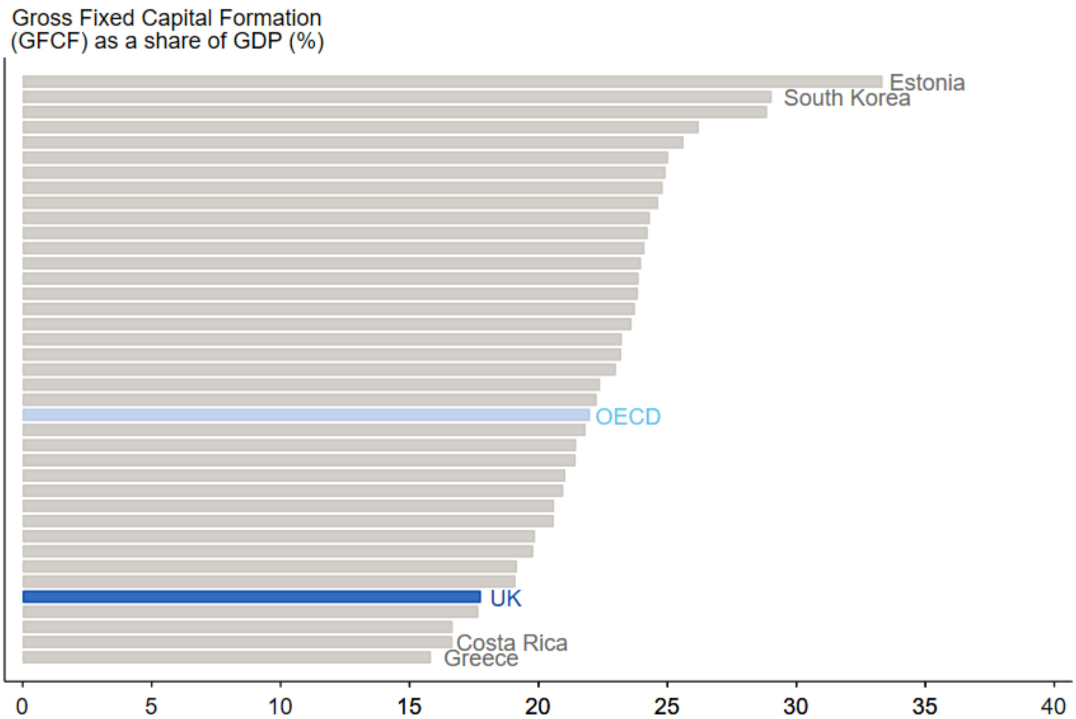
7.10 This section brings together cross-country comparisons for the other pillars of the growth mission: investment, people, stability, place, innovation, Net Zero and trade (which forms one growth pillar with industrial strategy).

7.11 First, we turn to investment. Figure 7.1 shows the rate of Gross Fixed Capital Formation (GFCF), a standard national accounts measure of investment, as a share of GDP, across OECD countries in 2023, the latest year available. Both private and public investment are included in this figure.

7.12 With an investment rate of about 18%, the UK sits well below the OECD average of about 23%, and even further behind the leader, Estonia, at 33%.

Figure 7.1: The UK has a lower investment rate than most OECD countries

Gross Fixed Capital Formation as a share of GDP, UK and OECD peers, 2023, from the OECD and World Bank databases



Calculated using real Gross Fixed Capital Formation (GFCF) and real GDP data for 2023 in *USD*, with 2015 reference prices.
Sources: *World Bank* (2023); *OECD* (2023).

7.13 Figure E.33 in the appendix shows that the UK's investment shortfall is not specific to a particular year. Instead, the UK has underinvested compared to peer countries for many years.

7.14 Alayande and Coyle extend an internationally comparative data series on investment back to the 1980s and argue that in fact the UK's investment shortfall has deep roots, starting over thirty years ago.

7.15 However, researchers like Corrado, Haskel, Jona-Lasinio and Iommi have argued that this standard measure of investment can be misleading, particularly for service-heavy economies such as the UK. This is because investment in much of the assets of a modern, intangible economy (such as good management practices, job training, brand values and wider innovation practices) are not included in standard national accounts measures of GFCF.

7.16 Figure 7.2 shows how investment rates change once we use this wider definition of investment, using data from the EU KLEMS and INTANProd database by Bontadini, Corrado, Haskel, Iommi and Jona-Lasinio. The chart shows GFCF as a share of gross value added (GVA).

7.17 While the UK still lags the US and France on this measure, it does comparatively better. In recent years the UK seems to have overtaken Italy once wider intangibles are considered and finds itself on par with Germany.

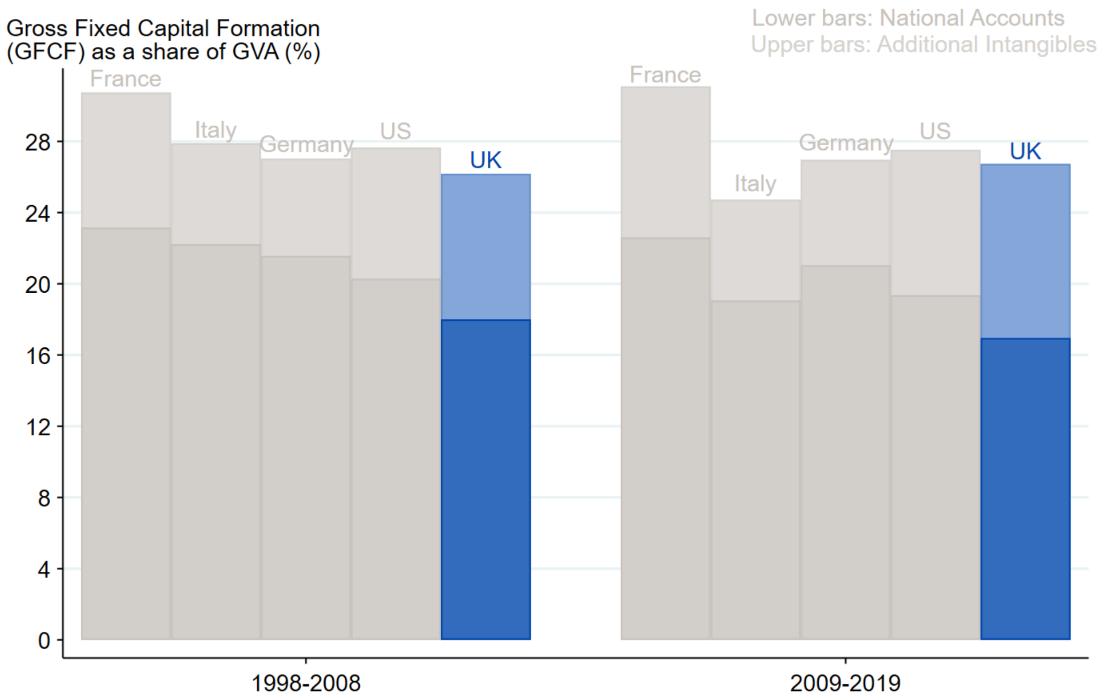
7.18 This suggests a deeper understanding of the desired type of investment is needed: building on the UK's strengths would mean greater investment in intellectual property, organisational practices, and branding. By contrast, addressing the UK's weaknesses means investment in physical assets and formal R&D.

7.19 Infrastructure investment is often seen as especially important, due to its ability to crowd in private investment and provide wider spillovers. Crafts reviews the case for greater UK transport infrastructure spending and argues that the UK would benefit from greater public spending in this area.

7.20 Pisu, Pels and Bottini compare UK infrastructure spending with that of OECD peers and find that in the UK, it is predominantly financed by the private sector, falls short of the OECD average, with lower perceived quality and potential capacity problems in some sectors.

Figure 7.2: When a wider definition of intangible assets is accounted for, the UK performs somewhat better on investment

Tangible and intangible investment as a share of GVA, UK and OECD peers, 1998-2019, from the EUKLEMS and INTANProd database



Average gross fixed capital formation (GFCF) as a share of Gross Value Added (GVA) (%) in the sub-periods 1998-2008 and 2009-2019. Full coloured bars represent national accounts measures of GFCF. Transparent stacked bars represent the increase when accounting for additional intangible investments. Real GVA volumes with 2015 reference prices is adjusted to account for intangibles. Countries are ranked in descending order in each sub-period. Sources: *EUKLEMS INTANProd database* (1998-2019).

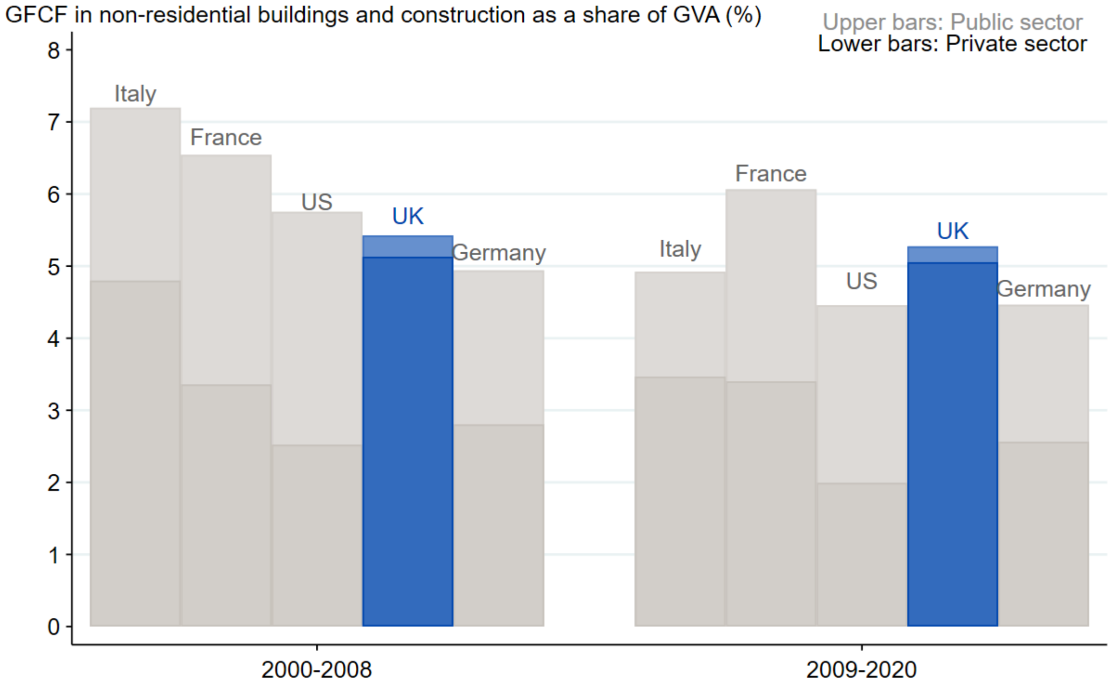
7.21 Figure 7.3 plots the latest non-residential construction investment rates for the UK and OECD peer economies. In line with Pisu, Pels and Bottini, we find that the UK invests relatively less in this area than most of its peers (although the difference has disappeared in recent decades due to falling investment elsewhere).

7.22 The UK is also much more likely to undertake investments in non-residential buildings and construction through the private sector than its peers, with over 90% of spending coming from the private sector, compared with about 50% elsewhere. Results do not change substantially when accounting for residential investment, as shown in Figure E.34 in the appendix.

7.23 Second, we turn to the people pillar. We first look at education expenditure, which is more easily measurable, and then at skills, a wider and more complete measure of bottlenecks in the economy.

Figure 7.3: UK investment in non-residential buildings and construction is generally lower than in peer countries, and predominantly provided by the private sector

Investment in non-residential buildings and construction as a share of GVA, public and private sector, UK and OECD peers, 2000-2020, from the EUKLEMS and INTANProd database



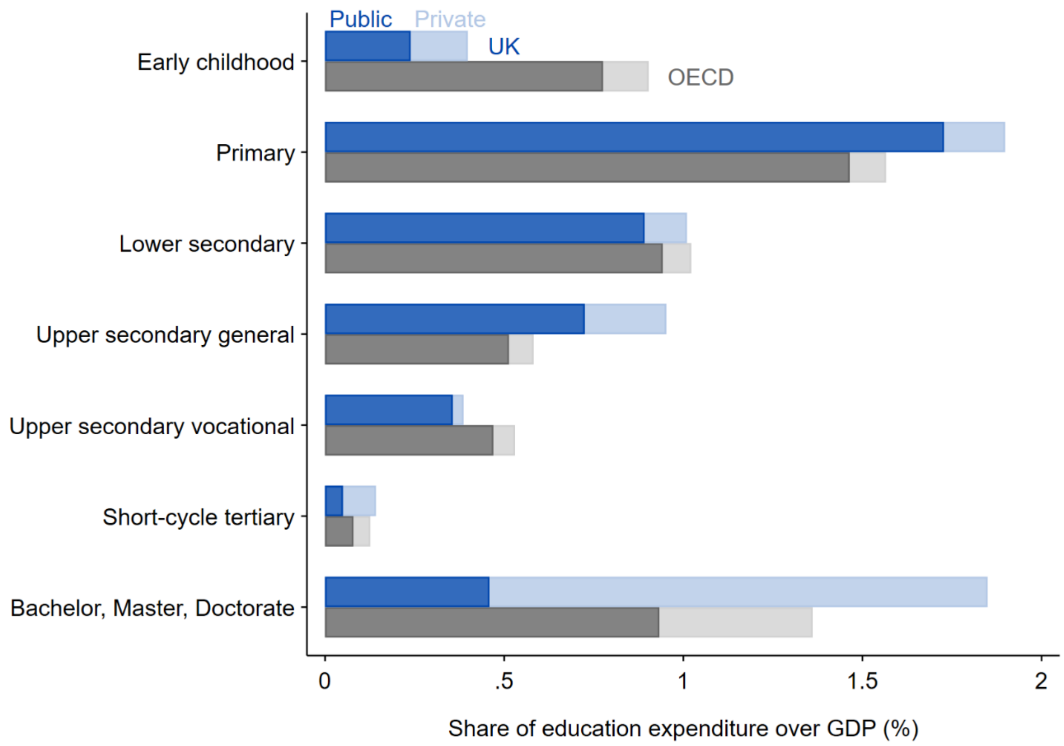
Gross fixed capital formation (GFCF) in infrastructure as a share of gross value added (GVA) (%), averaged over the sub-periods 2000-2008 and 2009-2020. GFCF and GVA are volume measures (prices of 2020). Public investment is proxied by that in Public administration, defence, education, human health and social work activities sectors (O-Q). Private sector excludes residential investment in real estate. Public is investment of sections O-Q. Source: *EUKLEMS & INTANProd database*.

7.24 Figure 7.4 shows spending at different levels of the UK education system, compared to the OECD average. Three differences are striking: First, the UK invests significantly more in university education than other OECD countries. Second, a much larger share of the higher education spending comes from private rather than public sources. Finally, the UK spends significantly less than other OECD countries on early childhood education.

7.25 Education expenditure is an important input into the people pillar, but perhaps a better measure of potential bottlenecks in the growth-driving sectors is the supply of skills compared to their demand in the economy.

Figure 7.4: The UK outspends peers on university education, predominantly from private sources, and lags behind in early childhood education

Public and private education spending, UK and OECD, 2020, from OECD education statistics



Source: *OECD Education Statistics* (2020)

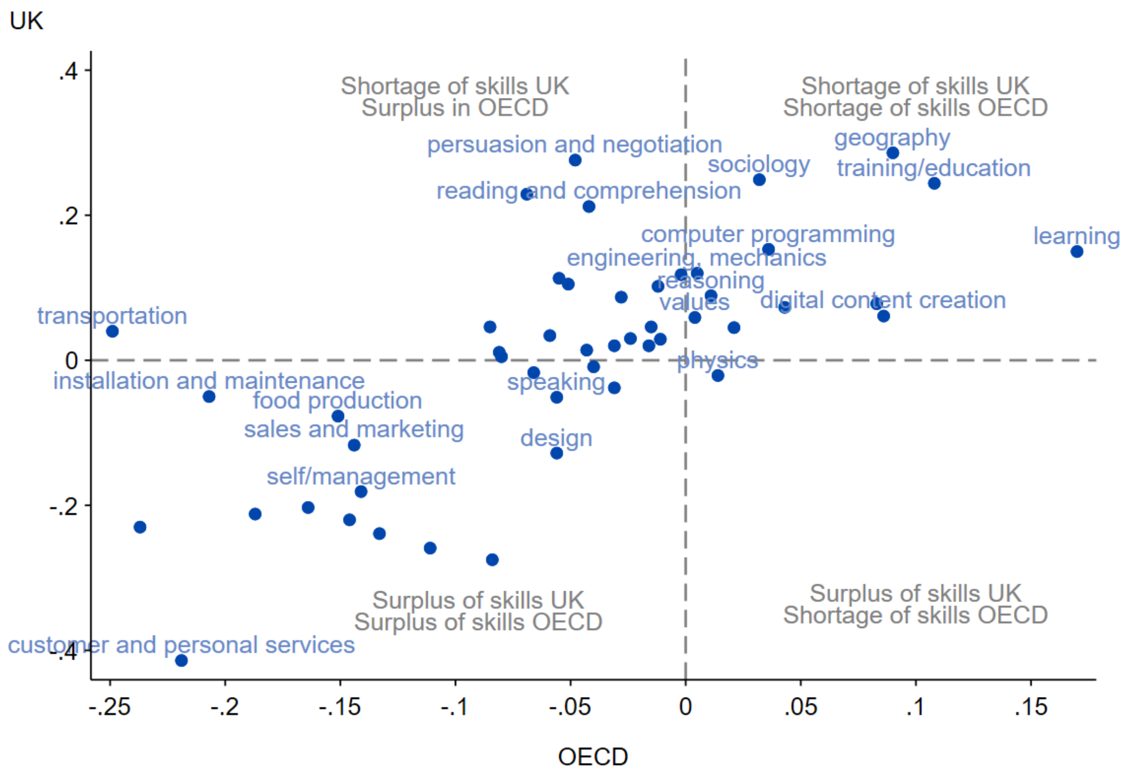
7.26 Figure 7.5 plots this relative measure of skill demand (constructed from a variety of sources, including job vacancy text data) in the UK and the OECD. Where a skill type is in short supply in the UK, it will appear in the upper half of the figure; where it is in short supply in the OECD, it will appear in the right half.

7.27 Some skills are scarce everywhere (shown in the top right quadrant): training/education, computer programming, digital content creation, engineering, mechanics, and sociology. Other shortages are UK-specific (top left quadrant): persuasion and negotiation, reading, construction and transportation.

7.28 To the extent that the UK government wants the growth-driving sectors to expand their employment footprint while maintaining or growing productivity, skills shortages (for instance in computer programming, digital content creation and engineering mechanics) may need to be addressed.

Figure 7.5: Among others, the UK has skills shortages in reading, computer programming and construction

Skills imbalances, UK and OECD, 2022, from the OECD Skills for Jobs database



Source: Skills for Jobs 2022, OECD. Skill imbalances measure the extent to which skills are in shortage, surplus, as well as mismatch in 2022 in OECD countries. Skill imbalance indicators are computed using a skill-occupation mapping using skill keywords retrieved from online job postings for the years 2012-2019. The occupational imbalance indicators are derived for 2-digit ISCO-08 categories, and consider the median wage growth, employment growth, hours worked growth, change in unemployment, and under-qualification rate.

7.29 Third, we turn to economic stability. When businesses are uncertain about the future, they invest less, particularly in risky, high-payoff ventures. Bloom, Bond and Van Reenen for instance argue that uncertainty reduces the responsiveness of businesses to demand shocks. The effect on investment can be large and diminish the effectiveness of public policies, including industrial policies.

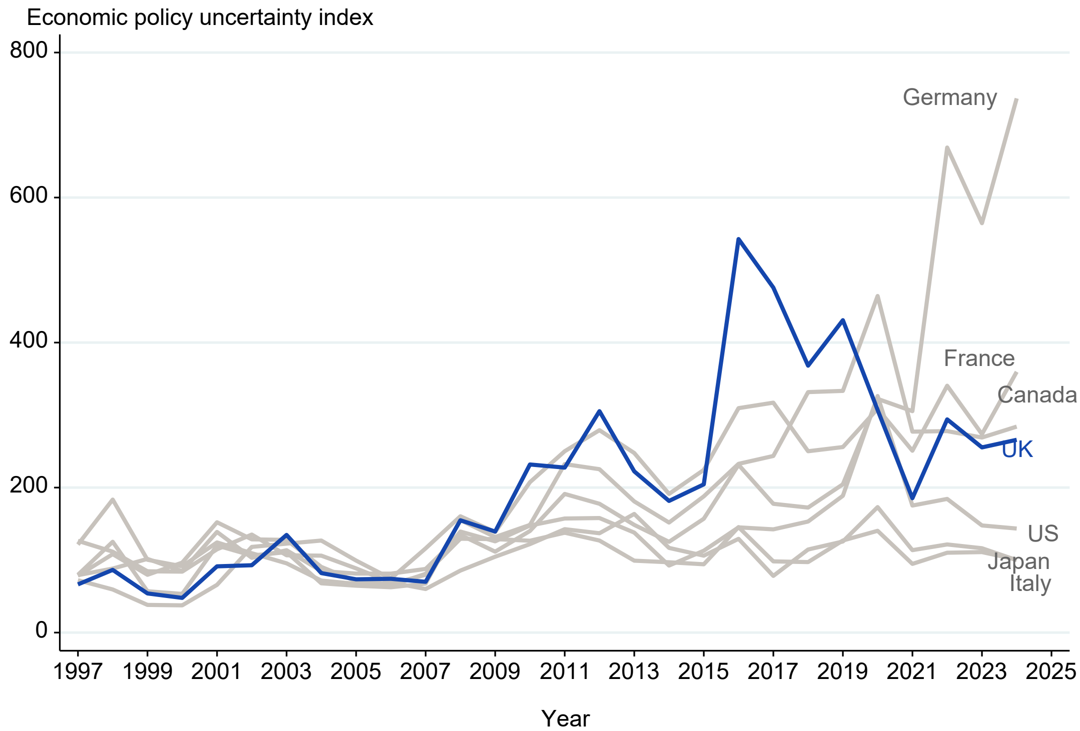
7.30 To measure uncertainty at the macroeconomic level, we rely on a frequently-used economic policy uncertainty index developed by Baker, Bloom and Davis. This metric is based on a large body of newspaper coverage, and measures how often expressions of economic uncertainty appear in articles covering economic policies.

7.31 Figure 7.6 shows that economic policy uncertainty has dramatically increased globally since 2007. The UK, previously characterised by high certainty, saw a spike in the wake of the Great Financial Crisis, and then again following the EU Exit referendum in 2016. In recent years, Germany, France, and Canada have overtaken the UK when it comes to economic policy uncertainty.

7.32 Some researchers, like Coyle and Alayande, argue that the UK's past economic policies have been characterised by uncertainty and policy churn at the microeconomic level too. Unfortunately, no comparative studies exist that test this claim quantitatively.

Figure 7.6: UK economic policy has become much less certain since 2008

Economic policy uncertainty index, UK and OECD peers, 1997-2024, from the Economic Policy Uncertainty database



Source: Economic Policy Uncertainty Database (Baker,S. Bloom, N. and S. Davis). Annual averages from monthly data.

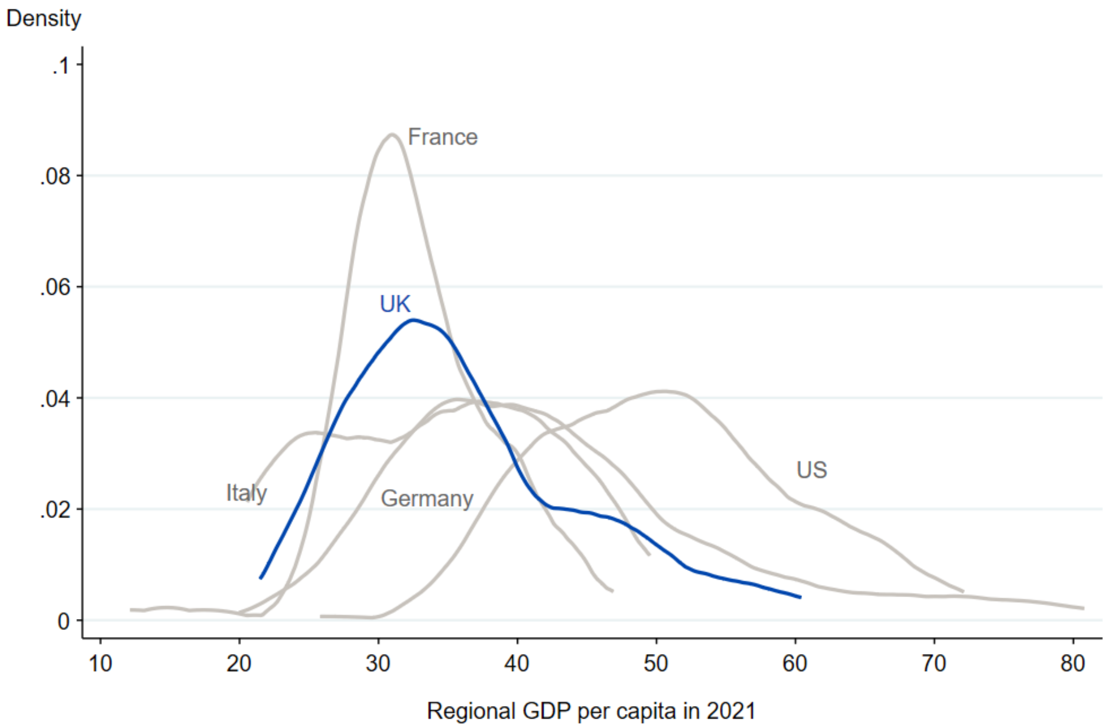
7.33 Fourth, we turn to the place pillar of the growth mission. This report has already discussed regional differences in both past industrial policies and the distribution of employment in the growth-driving sectors and industries upstream and downstream. The role of broader regional inequalities in holding back the UK's growth performance has also been widely discussed in research and policy circles.

7.34 For instance, Stansbury, Turner and Balls highlight the lack of transportation infrastructure in major non-London conurbations, a lack of support for regional R&D clusters outside the South East and the lack of intra-UK labour mobility caused by rising London housing prices as key pieces of the puzzle.

7.35 However, the relative severity of the UK's regional inequality in a wider context is open to discussion. Figure 7.7 shows that different European countries perform differently across different parts of the distribution of regional value added per capita. As a result, Figure E.35 and Figure E.36 in the appendix show that both comparative levels and relative trends in regional inequality are sensitive to the measure used. Population-weighting does not alter these conclusions, as Figure E.37 in the appendix shows.

Figure 7.7: Regional GDP in the UK is predominantly driven by a long upper tail

Density plot for regional GDP per capita, UK and OECD peers, 2021, from the OECD regional database



In thousand *USD*, 2015 prices, Purchasing Power Parities. Computed using data for ITL3 regions. For each country, we drop regions with a GDP above the 95th percentile. Source: *OECD Regional database* (2021).

7.36 Regional inequality is however not only a matter of GDP-per-capita levels. Figure 7.8 focuses on the number of high-growth firms, defined as firms with an average employment growth of over 20% per year over a three-year period. High-growth firms are often seen as crucial for providing innovation, productivity growth and high-wage jobs.

7.37 UK high-growth firms are predominantly concentrated in London: there are more than twice as many high-growth firms per 100,000 people in London than in any of the devolved nations or the North East of England.

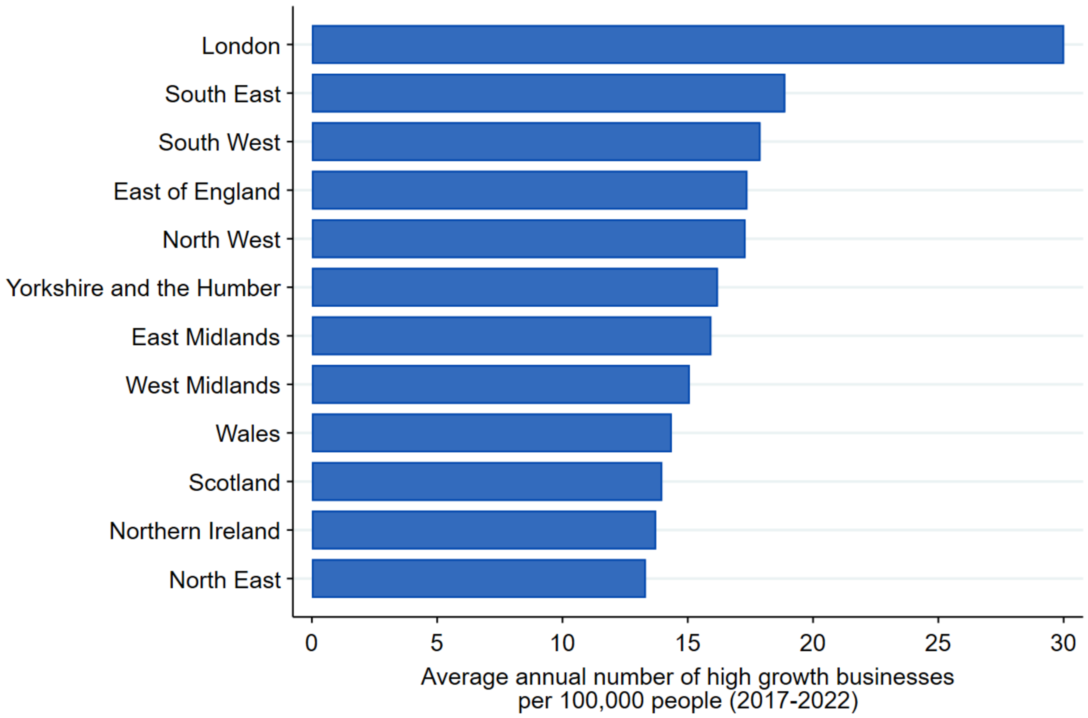
7.38 Figure E.38 in the appendix shows the raw number of establishments. Because London and the South East are more densely populated than other regions, regional differences are even starker here.

7.39 Using US firm-level microdata, Haltiwanger, Jarmin, Kulick and Miranda underscore the importance of high-growth firms for business dynamism and productivity growth.

7.40 Therefore, if regional differences in the prevalence of high-growth firms are driven by deeper, structural economic factors, they may lower the overall rate of dynamism and productivity growth in the UK economy.

Figure 7.8: High-growth businesses are concentrated in London

High-growth businesses per 100,000 people, UK regions and nations, 2017-2022, from the ONS local indicators dataset



High growth businesses are defined as those with an average growth in employment of greater than 20% per year over a three-year period. Normalisation uses 2022 regional population estimates. Sources: *ONS Local Indicators dataset* (2017-2022); *NOMIS Population Estimates* (2022).

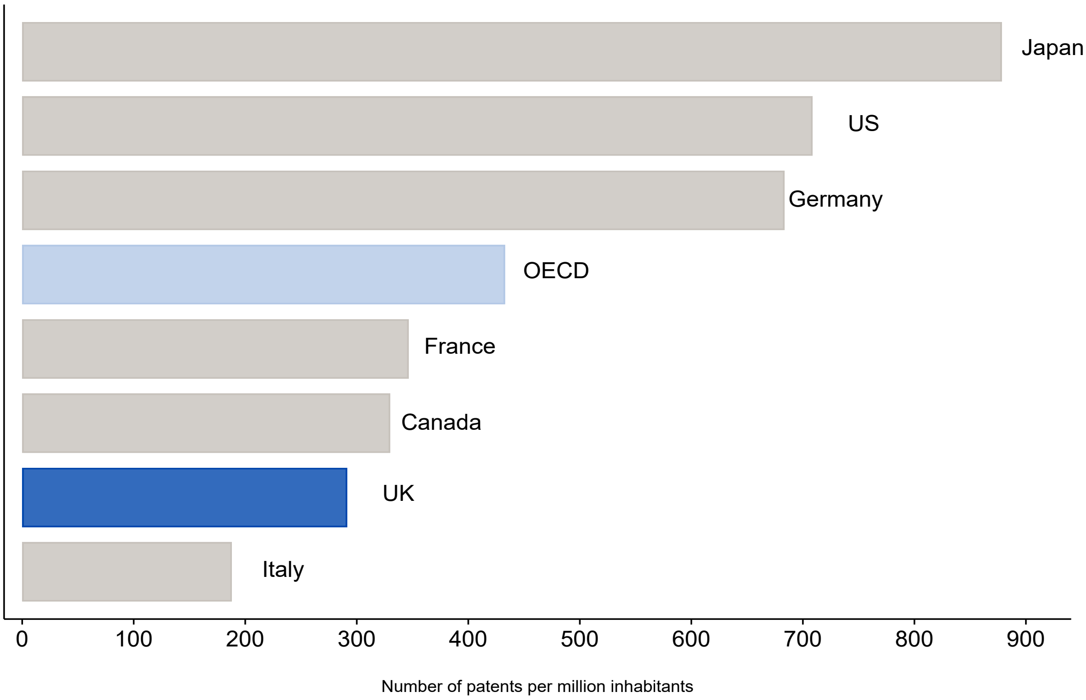
7.41 Fifth, we turn to innovation. For this discussion, we focus on patents, an outcome-based measure of innovation. Patents have some shortcomings: not all innovation is patented (or even patentable), and some patents are strategic (that is, designed to fend off competition rather than to protect truly novel work).

7.42 Nonetheless, patents are widely used as a benchmark of innovation among researchers and policymakers (see for example Autor, Dorn, Hanson, Pisano and Shu, or Acemoglu, Akcigit and Kerr).

7.43 Figure 7.9 shows the average number of patent applications per million inhabitants, for seven major OECD countries. Japan leads the field with nine hundred patent applications per million inhabitants, followed by the US and Germany with about seven hundred each. The UK sits at about three hundred, well below the OECD average of about 450.

Figure 7.9: The UK lags behind other OECD countries in the number of patents filed

Patents per million inhabitants, UK and OECD peers, 2013-2021, from OECD patents data



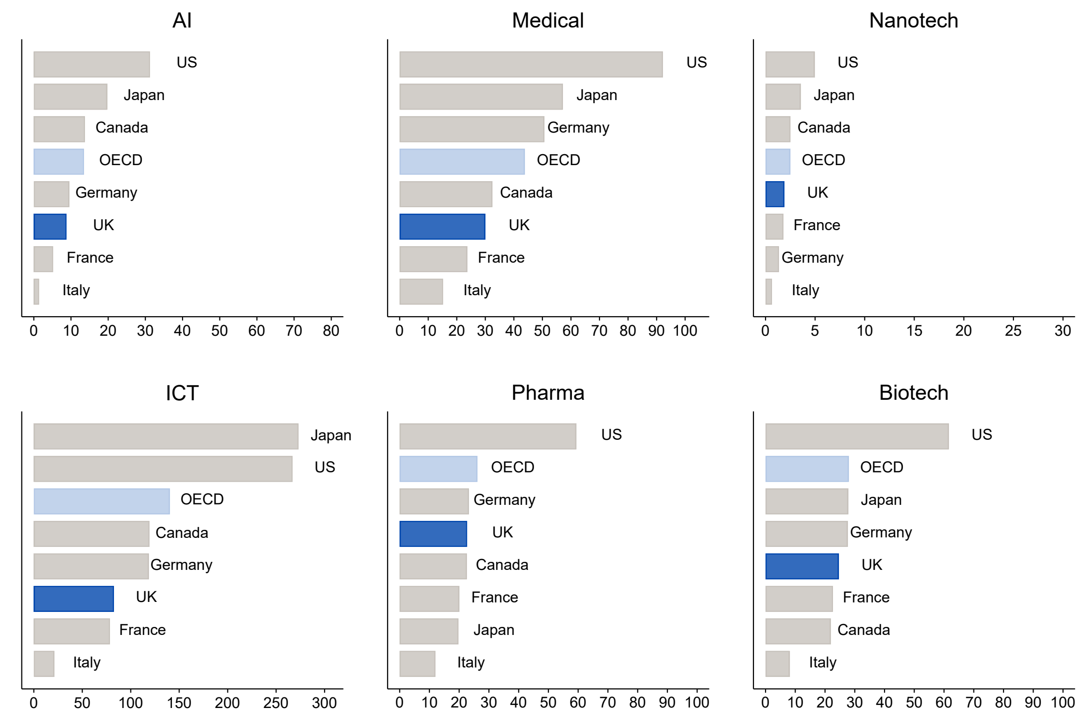
Source: OECD from patents applications at European Patent Office, US Patent Office and WIPO for selected techcnologies.
Number of patents per million inhabitants as an annual average for the period 2013-2021.

7.44 As Figure 7.10 shows, the same general picture is true for six key areas of emergent technologies: AI, pharma, medical, nanotechnology, information and communications and biotechnology. Per-capita patent rates in the UK are below the OECD average in all six.

7.45 Patents only measure a small and very particular number of innovations. For instance, Igami and Subrahmanyam examine the hard-drive industry and conclude that while patents convey some information about innovation, they generally underestimate innovation by small firms, and patent law reforms make comparisons over time difficult. Focusing on patents alone therefore may present a distorted view on innovation.

Figure 7.10: The UK lags behind other OECD countries in the number of patents

Patents per million inhabitants, selected patent classes, UK and OECD peers, 2013-2021, from OECD patents data



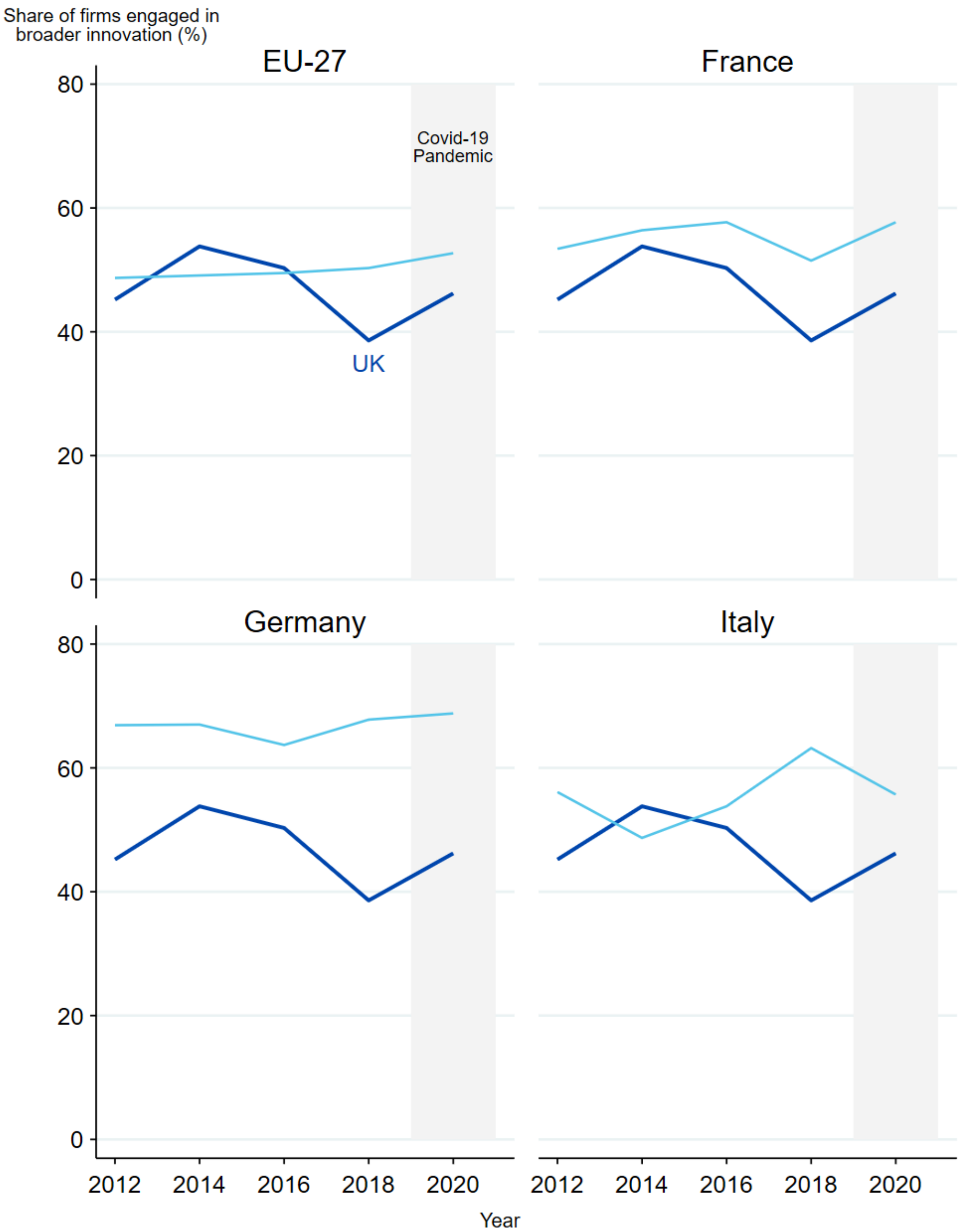
Source: *OECD, from patent applications at European Patent Office, US Patent Office and WIPO* for selected technologies. Number of patents per million inhabitants as an annual average for the period 2013-2021.

7.46 Figure 7.11 shows the share of firms engaged in wider forms in innovation between 2012 and 2020, for the UK and four peers, for which comparable data is easily available: France, Germany, Italy, and the wider EU.

7.47 At about 50% in 2020, a smaller share of UK firms actively pursues innovation than is the case for French, German, Italian or European firms. This suggests the UK's innovation gap is a broad-based problem and not limited to patentable innovations only.

Figure 7.11: A smaller share of UK firms is engaged in broad innovation than in other European countries

Share of firms engaged in innovation, UK and European peers, 2012-2020, from the UK Innovation Survey and Community Innovation Survey



Source: *UK Innovation Survey* (2012-2020) for UK and *Community Innovation Survey* (2012-2020) for EU-27, France, Germany and Italy.

7.48 Sixth, we turn to the Net Zero pillar. There are two ways to examine the UK's performance in this category. The first is to look at CO2 emissions per capita. This indicates how green the UK's economy is in producing goods and services on average, including outside the green-economy sector.

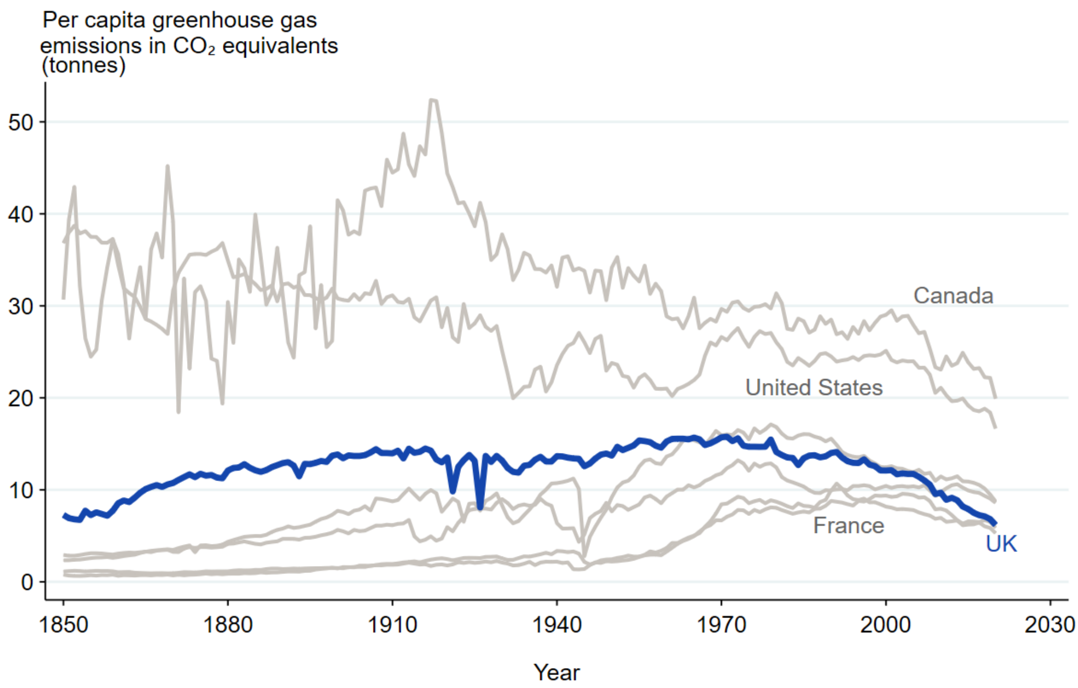
7.49 As Figure 7.12 shows, the UK has made steady progress by this count in recent decades and is now one of the leaders worldwide.

7.50 The UK's trajectory towards Net Zero potentially may have more direct economic benefits too. Curtis and Marinescu estimate that narrowly defined green jobs tripled in the US between 2010 and 2012 and pay on average a 21% wage premium.

7.51 Green investments however do not always benefit the local economy where they are made. Fabra, Gutiérrez Chacón, Lacuesta and Ramos study green investments in Spain and find no effects on the local economy, suggesting that firms bring in workers from further afield.

Figure 7.12: UK per capita greenhouse gas emissions have declined dramatically since the 1980s

Per capita greenhouse gas emissions, UK and OECD peers, 1850-2020, from Jones, Peters, Gasser, Andrew, Schwingshackl, Gütschow, Houghton, Friedlingstein, Pongratz, Le Quéré (2023), with processing by Our World in Data



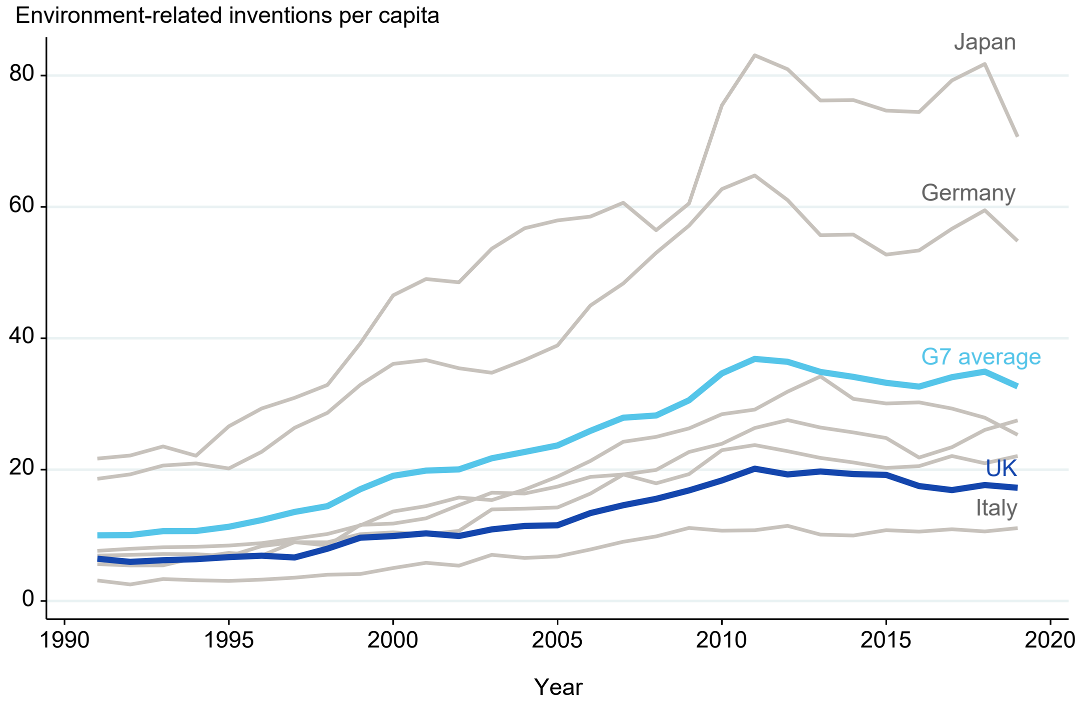
Source: *Jones, Peters, Gasser, Andrew, Schwingshackl, Gütschow, Houghton, Friedlingstein, Pongratz, Le Quéré* (2023), with processing by *Our World in Data*. Greenhouse gas emissions are measured in carbon dioxide equivalents (CO_2eq), which weight each gas by its warming potential over 100 years to reflect total climate impact. Countries included: Canada France Germany, Italy, Japan, United Kingdom and United States.

7.52 The second way to look at the UK's economic performance on this issue is as a participant in the green economy: that is, an innovator of goods and services that enable the transition to Net Zero.

7.53 On that basis, the UK's performance has been less strong. Figure 7.13 shows the per-capita number of green inventions over the last thirty years, compared to OECD peers. While growing, the UK still lags the OECD average, and lies far behind the leaders, Japan and Germany.

Figure 7.13: The UK underperforms OECD peers in the terms of per-capita green inventions

Per-capita environment-related innovations, UK and G7 peers, 1991-2019, from OECD Data Archive



Source: *OECD*. The number of environment-related inventions is expressed per million residents. Statistics are constructed by the OECD Environment Directorate from the OECD STI Micro-data Lab: Intellectual Property Database. Includes Technologies relevant to environmental management, climate change mitigation, climate change adaptation, and ocean sustainability.

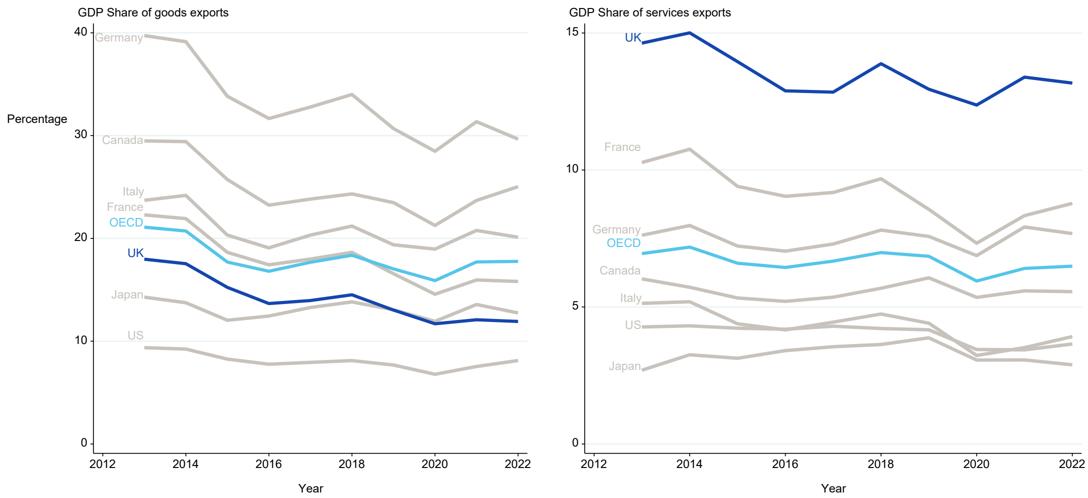
7.54 Kunapatarawong and Martínez-Ros find significant positive employment effects of green innovation among Spanish firms, particularly in heavily polluting industries. This suggests that encouraging green innovation, rather than simply green production, may be key to wider growth effects.

7.55 Finally, we turn to economic trade, which forms a growth pillar with industrial strategy. Figure 7.14 shows export shares, relative to GDP, for a range of peer economies. We separately plot goods exports and services exports.

7.56 When it comes to goods, the UK lies below the OECD average. This difference has increased slightly since 2016. When it comes to services, the UK’s service export share is nearly twice that of the OECD average. The UK’s lead on this dimension has however decreased by a few percentage points since its peak in 2014.

Figure 7.14: Compared to its GDP, the UK is a leader in service exports, but not in goods exports

Service and goods exports as a share of GDP, UK and OECD peers, 2013-2022, from the OECD Data Archive



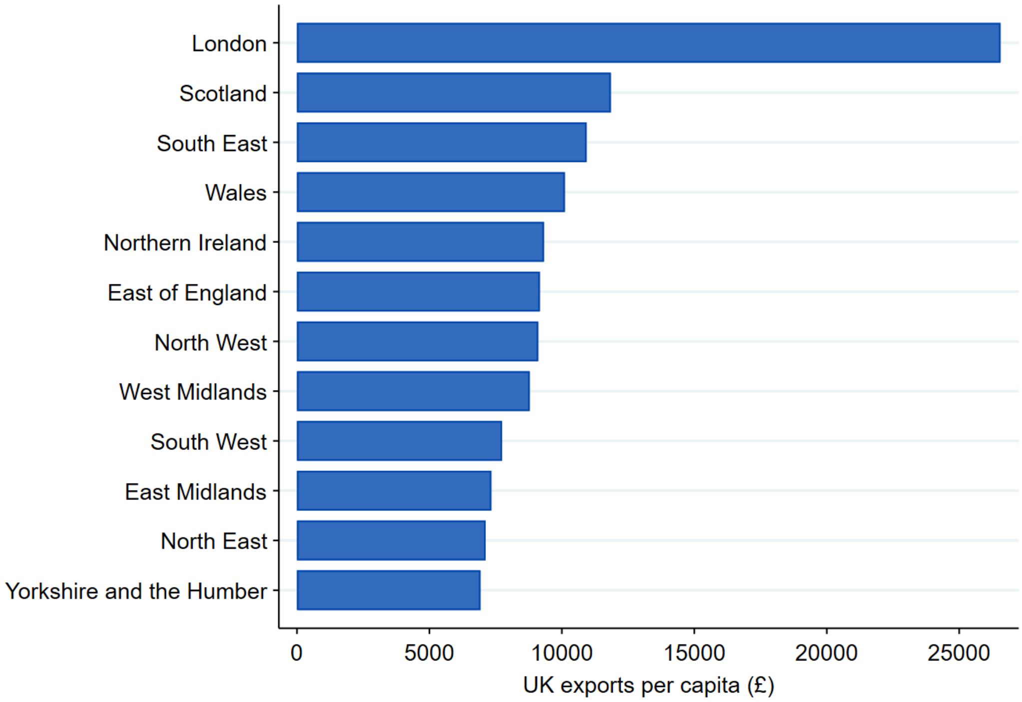
Source: Trade in goods and services in billion US Dollars, GDP in billion US Dollars.*OECD Data Archive*.

7.57 There is an important regional dimension to trade too. Figure 7.15 plots the UK's regional exports per capita in 2022, the last year available. Figure E.39 in the appendix shows the export shares without scaling by regional population.

7.58 Figure 7.15 shows London's disproportionate share of UK exports even after accounting for population differences. London's exports per capita are more than twice those of Scotland and over three times those of Yorkshire and the Humber. These findings suggest the need to consider interactions between trade and regional policies.

__Figure 7.15: UK exports are concentrated in London even after accounting for regional population differences__

Exports per capita, UK regions and nations, 2022, from the ONS local indicators dataset



Derived from estimates of the total value of UK exports including trade in both goods and services and regional population estimates.
Sources: *ONS Local Indicators dataset* (2022); *NOMIS Population Estimates* (2022).

Investment and skills are important bottlenecks in the growth-driving sectors

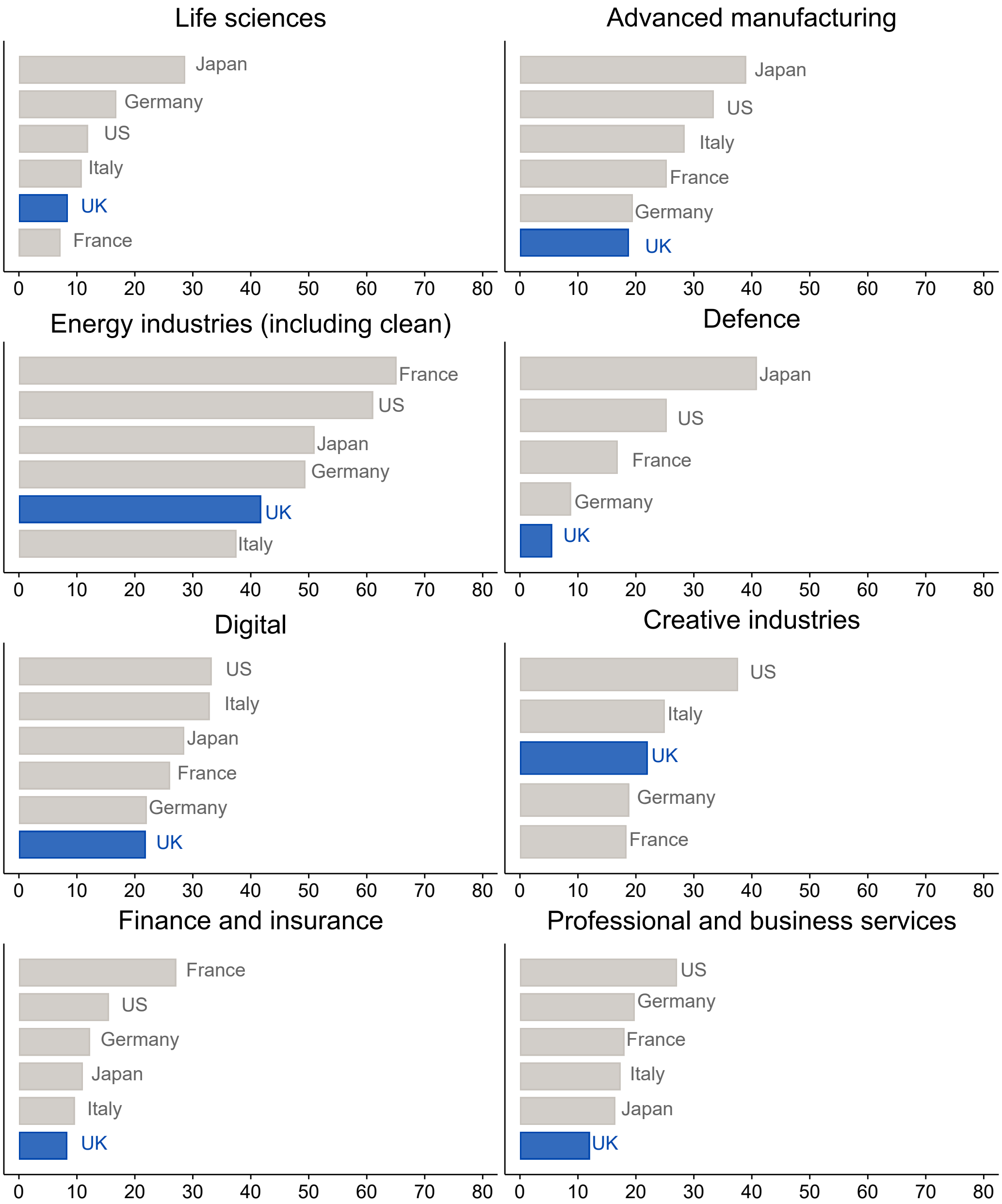
7.59 We want to understand the UK's comparative advantage on the other growth mission pillars not only at the aggregate level, but also where they can create bottlenecks for industrial policy at the growth-driving sector level.

7.60 A detailed industry-level analysis for all growth pillars is beyond the scope of this report. In this section, we focus on investment and skills, as they have been identified as areas of potential concern in the previous section. We bring together initial analysis on investment and skills for the growth-driving sectors and show that both present bottlenecks for some of the sectors.

7.61 Figure 7.16 shows investment rates (measured as Gross Fixed Capital Formation as a share of a sector's value added) for two-digit industry approximations of the growth-driving sectors, plotting the UK against peer countries: US, Italy, Germany, and France.

Figure 7.16: The UK has lower investment rates than peer countries even in the key growth sectors

Investment rates as a percentage of gross value added for the growth driving-sectors, UK and OECD peers, Average 2019-2022, from the 2025 OECD Structural Analysis (STAN) database



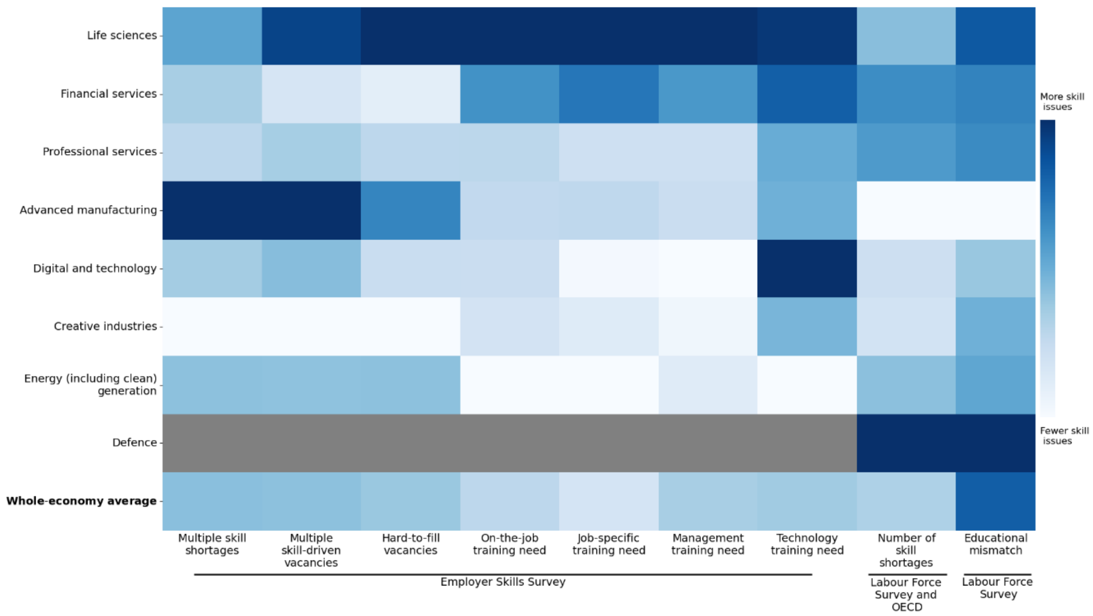
Source: OECD STAN 2025. Investment rate (%) is Gross Fixed Capital Formation over Value Added, mean 2019-2022. Life sciences includes human health activities, manufacture of medical and dental instruments and supplies; manufacture of irradiation, electromedical and electrotherapeutic equipment, manufacture of pharmaceutical products. Advanced manufacturing includes chemicals, pharmaceuticals, weapons and ammunition, computer, electronic and optical products, electrical equipment, machinery and equipment n.e.c., railroad equipment and transport equipment n.e.c.; air and spacecraft and related machinery, military fighting vehicles, medical and dental instruments and supplies. Clean energy industries in electricity, gas, steam and air conditioning supply only. Defence includes manufacture of weapons and ammunition; manufacture of military fighting vehicles. Digital includes Information and Communications. Creative industries include publishing activities; motion picture, video and television programme production, sound recording and music publishing, creative, arts & entertainment. Italy includes only publishing, motion picture, video and television. Professional services includes M-N SIC code, except veterinary services and scientific R&D. Results do not change significantly when including R&D.

7.62 Only in the creative industries is the UK in the top three among these countries. In the digital industries, professional services, advanced manufacturing, finance, and defence the UK comes last. This suggests that investment may indeed be a bottleneck, holding back performance in these sectors.

7.63 Figure 7.17 brings together skills data from a range of UK and international sources for the growth-driving sectors. These fall broadly into three categories: metrics that measure where employers struggle to fill specific vacancies; metrics that measure where employers need to provide various types of on-the-job training; and the mismatch between the education level employers look for and that of their employees.

Figure 7.17: Life sciences, financial services and advanced manufacturing have shortages in key skills

Measures of skill shortages and skill mismatch for the growth-driving sectors, UK, 2022, from the 2022 Employer Skills Survey, the 2022 Labour Force Survey and OECD Skills for Jobs database 2022



Source: multiple skill shortages, multiple skill-driven vacancies, hard-to-fill vacancies, on-the-job training need, job-specific training need, management training need and technology training need data come from the *Employer Skills Survey* 2022. Number of skills shortages is computed from the *OECD Skills for Jobs Database* mapped into industries using the occupational structure from the *Labour Force Survey* 2022. Educational mismatch is computed using the most prevalent qualification in occupations within industries from the *Labour Force Survey* 2022.

7.64 Because skill shortages and mismatch are particularly difficult to measure, we focus on the UK here and cannot provide like-for-like comparisons with international peers.

7.65 Compared to the whole-economy average, life sciences, financial services and advanced manufacturing all have comparatively high shortages and mismatches.

7.66 The defence sector is not covered by many of these measures, but where it is, it also shows important skill shortages and mismatches. This indicates that skills might be an important bottleneck to successful industrial policy spending in these sectors.

7.67 By contrast, the creative industries, digital and technologies and clean energy industries have relatively low skill shortages and mismatches, suggesting that skills are less likely to present a bottleneck here.

7.68 The analysis presented here chimes with a recent report by the National Audit Office (NAO) which analyses thirty-three internal government documents on the growth-driving sectors and identifies skills as the key barrier for many of them.

7.69 Costa, Datta, Machin and McNally argue that human capital tax credits, similarly to R&D tax credits, may be one way to address some of the market failures with regards to skills and therefore alleviate skills as a constraint on productivity growth.

7.70 This chapter has summarised the UK's relative performance on the other pillars of the growth mission. This information can inform the design of the UK's industrial strategy.

7.71 Once an initial industrial strategy has been designed, monitoring and evaluating industrial policies during and after implementation is equally important. We therefore turn to some important ongoing data and evidence gaps next.

8. What further work is needed to design and monitor industrial policies?

8.1 This report has brought together new evidence on the distribution and impacts of industrial policies, the characteristics of the UK government's growth-driving sectors, and the interplay of industrial policies and other pillars of the growth mission.

8.2 But important open questions remain. In this chapter, we first outline three further ongoing pieces of CMA research to support the UK government's industrial strategy. Then, we highlight remaining data and evidence gaps crucial for monitoring and evaluating the industrial strategy once in place.

Further CMA work to inform the industrial strategy

8.3 The CMA's Microeconomics Unit has announced three further pieces of research to support the UK government's industrial strategy and wider growth mission.

8.4 First, in recognition of the UK's documented investment shortfall, we are reviewing existing research on investment over the typical lifecycle of a business. This review will help policymakers understand how and where investment bottlenecks arise, and how competition in output, labour and financial markets shapes them.

8.5 Second, we are building new evidence on the diffusion of technologies both within and across UK industries. This is crucial for our understanding of spillovers, and therefore sustained and broad-based growth.

8.6 Finally, supply chains are crucial for the resilience of an economy, and for understanding spillovers and regional effects of growth policies. Therefore, we are undertaking new research to map UK supply chains to an unprecedented degree and understand how competition across them shapes the transmission of productivity and cost shocks.

Open questions and data needs for monitoring and evaluation

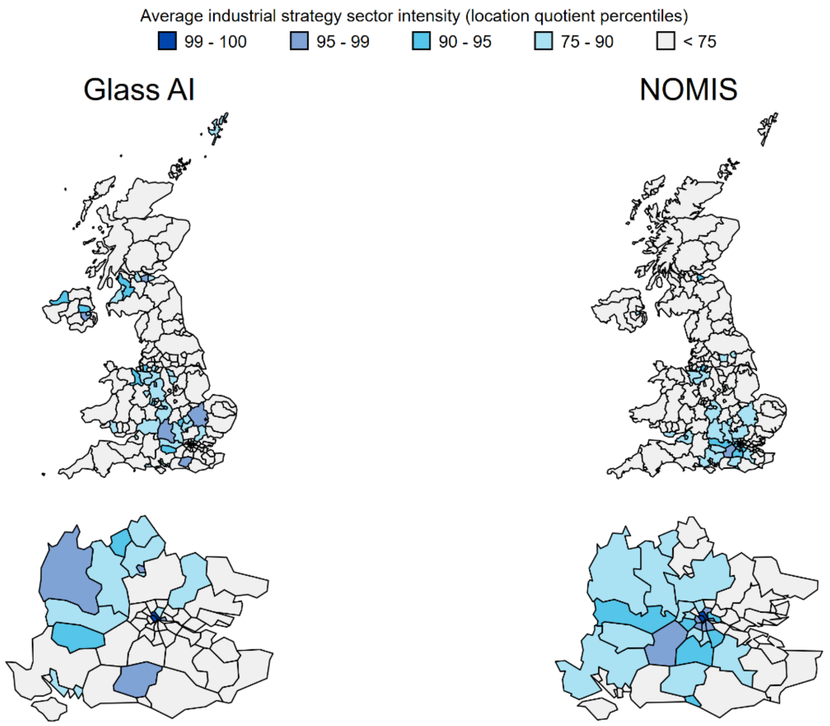
8.7 Policy cannot target what we cannot measure. Therefore, accurate sector designations are key to successful vertical policies. But traditional industry classifications, such as the Standard Industrial Classification (SIC) have limitations, particularly when it comes to measuring emergent sectors. This problem is inherent in the SIC system. Updated SIC definitions can alleviate but not solve it.

8.8 Figure 8.1 below shows the business establishment distribution across the growth-driving sectors, according to official ONS statistics (NOMIS), and using Glass.AI's deep search algorithm. In other words, the two maps show two different approaches to classifying firms according to their technologies and business activities and mapping them out across space.

8.9 The patterns are broadly similar, with the South East and West Midlands prominent in both maps, but there are also striking differences. For instance, Glass.AI's classification identifies businesses in Scotland and Northern Ireland not apparent from ONS data.

Figure 8.1: Official and web data are broadly in agreement, with some differences

Establishment location quotients for the growth-driving sectors, UK regions and nations, 2024, from Glass.AI and ONS NOMIS data



Location quotients showing the ITL3 regions in the UK and the South East of England with the highest average concentration of firm establishments in the eight sectors of the industrial strategy green paper. Sources: *Glass AI* 2024; *NOMIS UK Business Counts* 2024.

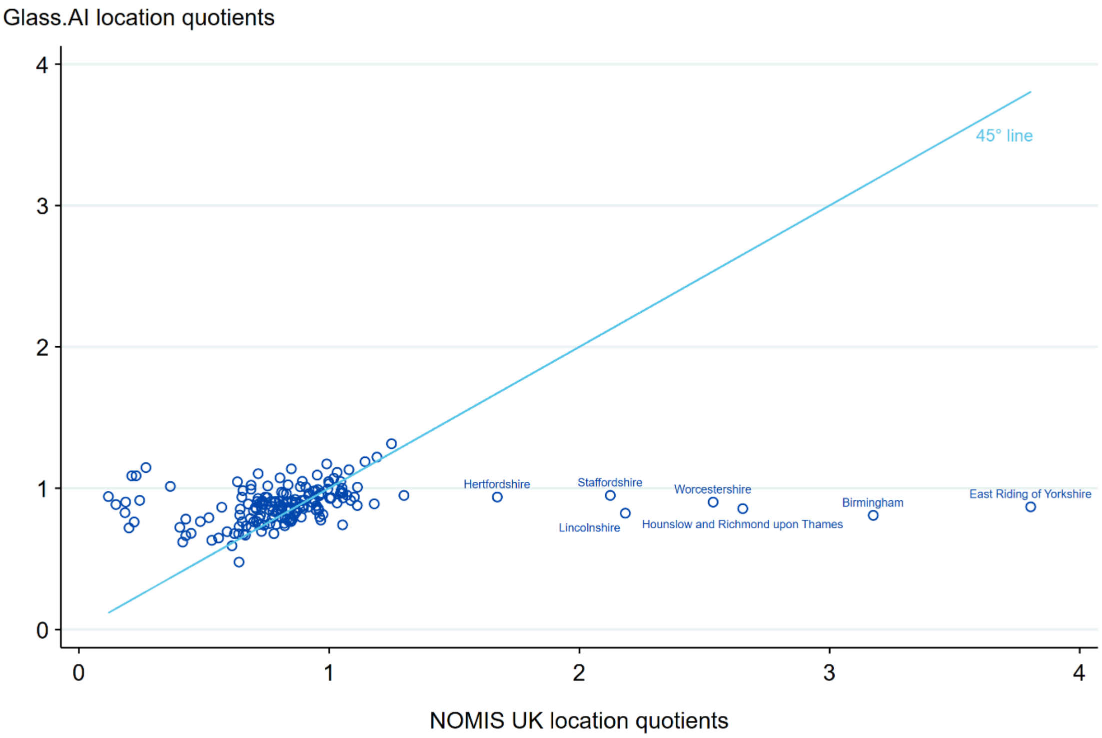
8.10 Figure 8.2 makes this comparison more general, by comparing location quotients for all growth-driving key sectors and all ITL3 regions between the two data sources.

8.11 If the two data sources assigned the same business establishments to each key sectors, all observations would lie precisely on the 45-degree line. Dispersion away from the 45-degree line indicates that traditional and web-based sources disagree.

8.12 Most observations lie on or close to the 45-degree line, suggesting that for most cases, the two data sources are indeed identifying similar businesses. However, there are several outliers where either official ONS statistics or web-scraped sources suggest higher firm counts in key sectors. This indicates that identifying relevant firms is not trivial.

Figure 8.2: Official and web data are broadly in agreement, with some differences

Establishment location quotients for the growth-driving sectors, UK regions and nations, 2024, from Glass.AI and ONS NOMIS data



Comparison of the location quotients for ITL3 (2021) regions computed using *Glass.AI* 2024 data and *NOMIS UK Business Counts* 2024.
45° line in light blue for reference.

8.13 Earlier work by Nathan and Rosso conducted a similar experiment for the digital sector, and found business counts to be over 40% higher in text-based sources than in official ONS business statistics.

8.14 Which classification is closer to reality is of course not yet clear. But the UK government will need more accurate data on key-sector firms, including young firms and start-ups, which are particularly difficult to capture in traditional data sources.

8.15 In addition to being able to correctly track businesses in targeted sectors, policymakers need to have the tools to assess in a timely manner if policies are working as intended.

8.16 In 2022, the National Audit Office (NAO) evaluated a range of local growth policies, including Levelling Up, the UK Shared Prosperity Fund and the Towns Fund.

8.17 It argued that reliance on data collected by local bodies hindered the evaluation of past local growth policies, and therefore future learning.

8.18 Our own report has noted the difficulties of evaluating industrial strategies in the abstract. Policies may be enacted for many reasons and targeted at industries and firms that have had quite different productivity paths to start with.

8.19 Where policy thinking has evolved beyond the "whether" to the "how", it might be more promising to evaluate specific past industrial policies, such as export support programmes or R&D tax credits, rather than estimate average effects across many types of policies.

8.20 By using deep knowledge about the programme design and the targeted industries, researchers can likely make more credible claims about the causal effects of these policies, as Juhász, Lane and Rodrik also suggest in their review article.

8.21 However, researchers should not exclusively study those policies seen as international successes. Omitting less successful cases may otherwise lead policymakers to overestimate the likelihood of successful policies.

8.22 The aforementioned NAO report evaluating local growth initiatives raised three specific concerns that may also apply to industrial policies more widely.

8.23 First, the NAO expressed concern about a tendency to prioritise "shovel-ready" projects over those with greater strategic value. Second, it argued that the fragmented nature of funding sources made it difficult for local authorities to fund long-term priorities in a joined-up way. Finally, it argued that due to the technicality of the projects, increased workload and staff turnover, the capacity and capability within relevant government departments was a key constraint for delivering successful outcomes.

8.24 This echoes recent research by Barteska and Lee, who argue that government capacity was a key ingredient in the South Korean growth miracle. A one standard-deviation increase in bureaucrat ability within a South Korean export promotion office boosted exports to the relevant country by an astounding 37%.

8.25 Juhász, Lane and Rodrik point out two additional reasons industrial strategies can fail. First, government may not possess all the information needed to make the right decisions on which sectors to boost, and how. Second, the development and implementation of industrial strategies may fall victim to political capture: through lobbying and influence activities, vested interests can distort the welfare-maximising design of industrial policies.

8.26 The recent NAO report on support for the growth-driving sectors likewise points to information as a key enabler of effective industrial policy, referring to the need to make better use of evidence on the effectiveness of different interventions, to have a more complete overview of existing business support programmes, and the importance of monitoring and evaluating the impacts of interventions.

8.27 At a time of increased global trade frictions, industrial strategies may also take on a geopolitical dimension. Liu, Rotemberg and Traiberman show using the example of semiconductor supply chains that hampering an economic rival via sabotage can under certain circumstances increase domestic incomes.

8.28 At the same time, Grossman, Helpman and Redding show that where supply chains form in anticipation of free trade, unexpected tariffs carry large costs in terms of supply chain disruptions.

8.29 But even in the best of cases, the design of industrial policy is complex. Aghion, Barrage, Hémous and Liu study the transition towards green technologies in a model with supply chains. The exercise reveals that targeted policies can help nudge the economy onto the right path, but that not targeting policies correctly along supply chains can lead to undesirable outcomes.

8.30 There are other considerations to designing effective industrial policies. In a recent review article, Coyle argues that given the current twin technology transitions (towards clean energy, and artificial intelligence), policy tools need to be better coordinated across different bodies, and political legitimacy needs to be balanced with expert input.

8.31 Coyle and Muhtar analyse past UK industrial strategy announcements and highlight the importance of certainty and coordination, which have often been lacking in the past.

8.32 Piechucka, Sauri-Romero and Smulders outline some principles to understand when industrial policies are efficiency-enhancing, and how to design them to be pro-competitive, using the transition to Net Zero as a guiding example. They stress proportionality, competitive tendering, and an eye to the risk of subsidy races.

8.33 The need to monitor industrial policies to ensure they are designed to be efficiency-enhancing and pro-competitive applies to the UK as well.

8.34 As a large body of research notes (Decarolis provides one recent example), the regulation of subsidies itself can influence the incentives of individuals or organisations involved. Often, this can take the form of "bunching": observations shifting from one side of a threshold to the other. Kleven explains the basic intuition for the broader case of tax thresholds.

8.35 Figure 8.3 shows the distribution of subsidies around the current £10m Subsidies and Schemes of Particular Interest threshold at which public bodies need to refer subsidies outside sensitive sectors to the Subsidy Advice Unit.

8.36 After legislation introducing the threshold passed in 2022, more subsidies appeared at or below the threshold value of £10m, compared to the previous year. By 2023, when the legislation entered into force, there were no subsidies with values between £10m and £10.5m.

8.37 Figure 8.3 cannot tell us whether the subsidy threshold is too high, too low, or set at the optimal level. We would also need more evidence before concluding that the introduction of the threshold caused subsidies to shift below it.

8.38 But Figure 8.3 suggests that rules can create incentives, which organisations may then react to, including sometimes in ways not foreseen when policies and institutions are initially created.

8.39 To the extent that subsidy amounts respond to the creation of a threshold, this indicates the importance of continuously monitoring the effectiveness not just of specific subsidies and industrial policies, but also of the frameworks and institutions charged with administering and supervising them.[6]

8.40 In this context, we note the work the CMA's Subsidy Advice Unit is doing to monitor the effectiveness of the UK's subsidy control regime, including its impact on UK competition and investment, with a first report due to be published in 2026.

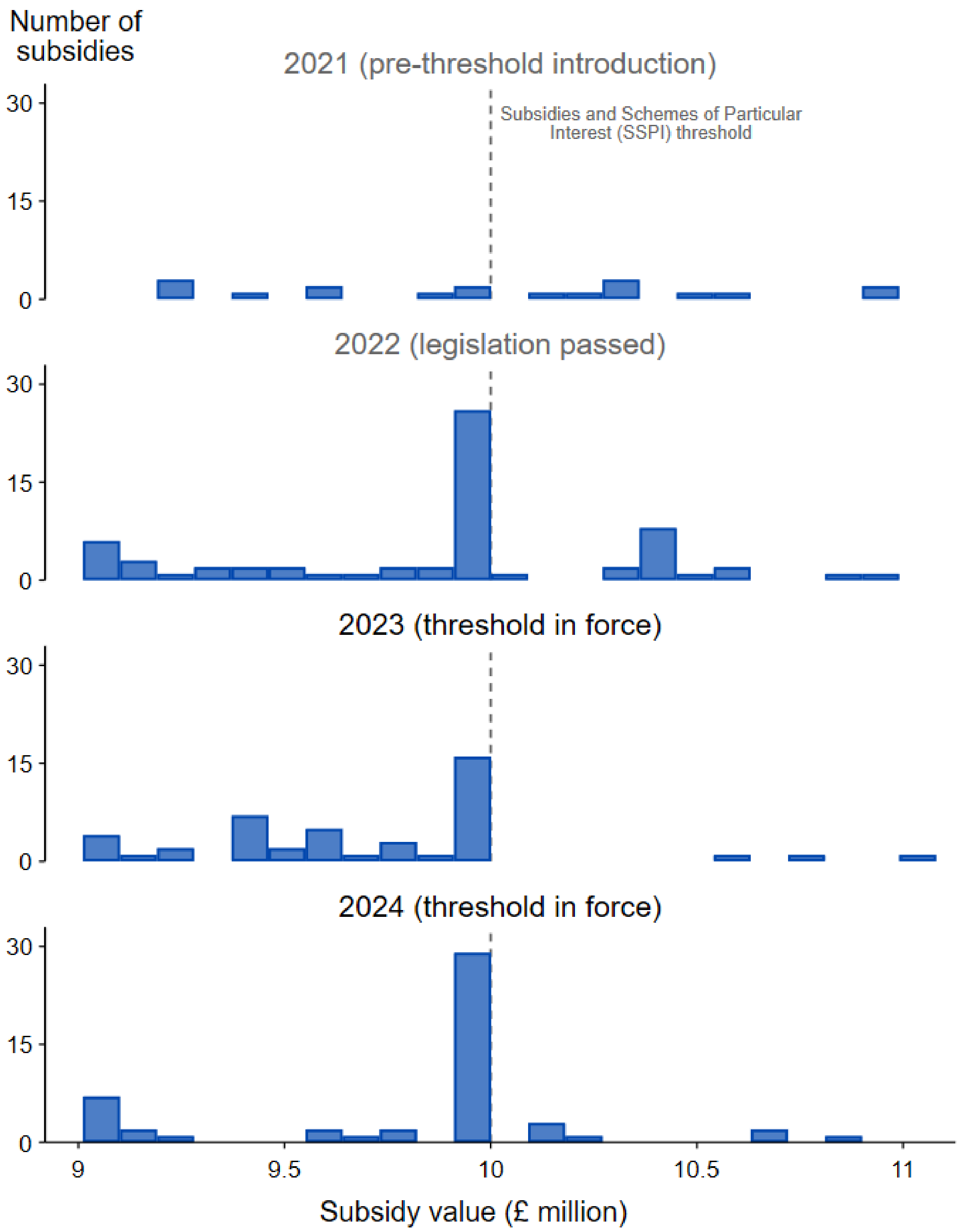
8.41 Thanks to increased research and policy interest, we know much more now than a decade ago about what makes industrial policies effective. This report builds on this work and provides new evidence to support the UK government's industrial strategy and wider growth mission. By building

[6] For instance, through DBT's recent consultation designed to refine the UK's subsidy control regime. In its consultation response, DBT proposed raising the non-sensitive mandatory reporting threshold from £10m to £25m, and creating new streamlined routes for certain subsidy types.

evaluation into policies, and expanding the research frontier, yet better policy design will be possible in the future.

Figure 8.3: After the Subsidies and Schemes of Particular Interest threshold is introduced, more subsidies appear below it than above

Subsidy counts around the £10 million threshold, UK, 2021-2023, from the UK Subsidy database



Distribution of subsidies around the £10 million threshold above which subsidies not within 'sensitive' sectors must be referred to the Subsidy Advice Unit. Sources: *EU State Aid Database* (2021– 2024); *UK Subsidy Database* (2021–2024). Source data is accurate to the database contents on 30 March 2025.

Table of Figures

A. Acknowledgements

A.1 This report was written by Rob Mitchell, Luke McWatters, Rajssa Mechelli, Marium Ashfaq, Isabelle Peek, Ana Rincon Aznar, and Jakob Schneebacher on behalf of the CMA Microeconomics Unit.

A.2 The authors are very grateful to Reka Juhász, Nathan Lane, Emily Oehlsen and Verónica Pérez for sharing their industrial policy classification of the GTA database, to the Competitiveness Research Network (CompNet) for access to the industry data from their distributed microdata project, and to Glass.AI for sharing data on establishment counts for their proprietary definition of the growth-driving sectors.

A.3 In addition, this report uses data from the Department of Education, the EUKLEMS and INTANProd project, the European Commission, EUROSTAT, the OECD, the ONS, the US Bureau of Labour Statistics and the World Bank. We would like to thank these institutions for providing public access to valuable datasets.

A.4 Finally, the authors would like to thank Russell Black, Esther Boler, Giacinta Cestone, Diane Coyle, Catherine van der List, Howard Smith, Joel Stiebale, Anna Valero, Robert Zymek and many CMA colleagues for their feedback on methods and results, Joel Kariel for help with supply chain data, Frank Donnarumma for feedback on data visualisations and Hugo Wallis for help and advice on drafting.

B. Glossary

B.1 **Business dynamism:** Business dynamism refers to the degree of churn in an economy. High levels of business dynamism are suggestive of a vibrant and competitive economy where new ideas are constantly introduced and resources such as capital and labour reallocated to their most productive use. We measure business dynamism through entry and exit rates, job reallocation rates and the persistence of large firms over time.

B.2 **Cost markups:** Economists define cost markups as the difference between the price at which a good or service is sold and its marginal cost. Cost markups are a measure of market power. In a perfectly competitive market firms set their prices equal to their cost of production, resulting in a ratio of price to marginal cost near one. Monopolists and oligopolists have positive markups (greater than one). For given fixed costs, the larger the markup, the greater the profit margin earned by the firm and the higher its market power.

B.3 **Establishment location quotient:** Location quotients measure the concentration of an industry within a specific area relative to the concentration of that industry nationwide.

B.4 **Gross Fixed Capital Formation:** Gross fixed capital formation measures resident producers' investments net of disposals in fixed assets during a given period. Fixed assets are produced tangible or intangible assets that are used repeatedly or continuously for more than one year.

B.5 **Gross Value Added:** Gross Value Added (GVA) is defined as output (at basic prices) minus intermediate consumption (at purchaser prices). The sum of GVA over all industries or sectors plus taxes on products minus subsidies on products gives gross domestic product.

B.6 **Industrial policy:** Industrial policies are policies implemented by governments to shape the industrial composition of the economy. While the term encompasses a wide range of interventions, often industrial policies describe measures that are selective (that is, that favour a specific industry, economic activity, technology or set of firms).

B.7 **Industrial strategy:** An industrial strategy is a collection of industrial policies designed to achieve a certain outcome, such as raising productivity. Industrial policies can be defined in narrower or broader terms, depending on whether they focus on specific vertical tools or include broader, horizontal policies.

B.8 **Network centrality:** Network centrality measures how important a node in a network is. This could be through the direct connections it has with other nodes in the network or through their connections in turn. In the case of a supply network, a node usually represents an industry.

B.9 **Returns to scale:** Returns to scale measure the change in output due to a given increase in all inputs. Returns to scale can be increasing (output increases more than proportionally), decreasing (output increases less than proportionally) or constant (output increases in the same proportion). Increasing returns to scale technologically favour larger firms, while decreasing returns favour smaller firms.

B.10 **Shift-share regression:** Shift-share analysis estimates the impact of a common event or policy by comparing units that for unrelated reasons are exposed differently to it. Frequently, although not always, shift-share designs exploit the fact that geographical regions are differentially exposed to national or global shocks due to pre-existing differences in their underlying characteristics, such as industrial composition or demography.

B.11 **Spillover effects:** Spillover effects are indirect effects of a policy or event on non-targeted entities (countries, regions, industries, firms, or even time periods). Spillovers can be positive or negative. Economists call non-monetary spillovers an externality.

B.12 **Subsidy:** The UK Subsidy Control Act (2022) defines a subsidy as an instance of a public authority granting financial assistance to an enterprise (whether directly or indirectly) from public resources. To be considered subsidies, financial assistance needs to be given directly or indirectly by a public authority, confer an economic advantage to is the recipients, needs to be targeted at specific recipients and be capable of affecting UK competition, investment or trade.

B.13 **Supply chain:** Many firms do not directly sell to consumers but instead sell to other firms. There may be many such business-to-business transactions before the final product reaches consumers. A supply chain covers the span of all intermediate transactions needed to go from raw inputs (upstream) to the final consumption product (downstream).

B.14 **Upstreamness:** Upstreamness measures the distance of a sector's production from the final consumer. It is usually computed using Input-Output tables, which describe transactions (sales and purchases) between producers and consumers of different goods and services.

C. Data sources

Industrial policy data sources

Global Trade Alert (GTA) database

C.1 The GTA database collects government statements/announcements, from 2008 onwards, which involve credible, meaningful and unilateral changes in the relative treatment of foreign versus domestic commercial interests in an industry or set of industries.

C.2 Since not all GTA entries are industrial policies, we complement the GTA database with a filtered version of the data provided by Juhász, Lane, Oehlsen and Pérez. The authors train a machine-learning algorithm on this text-based dataset to identify policies that explicitly aim to shape the composition of economic activity and are implemented at least at the national government level.

Quantifying Industrial Strategies (QuIS)

C.3 QuIS is a recent effort by the OECD to collect detailed information on industrial policies in member countries, including expenditures. The dataset includes eleven countries to date (Canada, Denmark, France, Germany, Ireland, Israel, Italy, the Netherlands, Slovenia, Sweden, and the UK) and covers the period 2019-2022.

C.4 QuIS defines industrial policy expenditures as "direct support extended by the public sector to businesses, aimed at promoting investment (including digitalisation and cleaner production), improving competitiveness, or supporting economic development."

UK Subsidy Database

C.5 The UK subsidy database includes information on subsidies awarded to businesses in the UK, in compliance with public authorities' obligations under the Subsidy Control Act 2022. The database covers subsidies from 2021 onwards, following the UK's exit from the European Union (EU). Prior to commencement of the Act, the database was maintained in accordance with provisions set out in the EU-UK Trade and Cooperation Agreement.

C.6 The UK subsidy database includes information on standalone subsidy awards, subsidies awarded under schemes, Minimal Financial Assistance awards (MFA) and Subsidies of Public Economic Interest (SPEI). In accordance with transparency rules, public authorities must upload information about a subsidy to a public transparency database. However, a limited number of subsidies are exempt from this requirement, including those that are:

- valued at £100,000 or less; and
- given out through a subsidy scheme (noting that any schemes would have their own entry) or as minimal financial assistance, or as a service of public economic interest.

C.7 Details of subsidy classifications, and exemptions to transparency rules, can be found in the Department for Business and Trade (DBT) statuary guidance for the UK subsidy control regime. Our reading of the guidance suggests that prior to January 2023, subsidy transparency rules were identical to the EU state aid transparency requirements (discussed below).

C.8 Our analysis of the UK subsidy database only considers the period 2021 – 2023 based on subsidy award/confirmation dates. We downloaded the datasets on 26 August 2024. Changes to the data after this date will not be reflected in the analysis. For the analysis shown in Figure 8.3, we downloaded the datasets on 30 March 2025.

EU State Aid Database

C.9 The EU State Aid database holds information on subsidies awarded by public authorities, in compliance with their obligations under the European Treaty and State Aid Transparency and Evaluation procedures. The EU State Aid database is maintained by the Directorate General for Competition and contains information for the following EU member states: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Sweden. Poland, Romania, Spain and Slovenia maintain their own national transparency databases.

C.10 A limited number of subsidies are also exempt from the transparency requirements of the EU database. The reporting threshold for most subsidies is €500,000, with thresholds of €60,000 for beneficiaries active in the primary agricultural production sector and €30,000 for beneficiaries active in the fishery and aquaculture sector. The EU database spans from July 2016 to the present. Datasets were downloaded for each EU country individually on 25 November 2024. Changes to subsidies recorded after this date will not be reflected in the analysis.

C.11 The EU database also contains certain UK subsidy data. This covers qualifying subsidies granted while the UK was a member state, and, following the UK's exit from the EU, subsidies that fall under the Windsor Framework (previously the Northern Ireland Protocol) and current awards under schemes managed by EU institutions, such as European structural funds. Our analysis finds no overlap between the UK database and EU database in the period 2021 - 2023. Consequently, we incorporate this data into the analysis of UK subsidies.

C.12 Our analysis excludes qualifying state aid issued by the European Investment Bank and aid involved in financial products supported by the InvestEU fund. Where the EU database provided a greater level of disaggregation of industry classification than the UK database, we aggregate the data to allow for accurate comparison.

The Spanish State Aid Database (Base de Datos Nacional de Subvenciones - BDNS)

C.13 The National System for State Aid and Subsidy Disclosure (El Sistema Nacional de Publicidad de Subvenciones y Ayudas Públicas - SNPSAP) contains data on subsidies provided by Spanish public authorities since July 2016.

C.14 In accordance with Spain's Article 3(b) of Law 19/2013 private entities receiving subsidies exceeding €100,000 in a single year, or when at least 40% of their total annual income consists of subsidies - provided this amount is at least €5,000 euros - must disclose information regarding the public aid received. The database also complies with the EU State Aid disclosure thresholds for subsidies. We queried the database API on 2 January 2025. To the extent that subsidies granted in the period 2016-2023 were modified after 2 January 2025, this will not be reflected in our analysis.

C.15 We use a combination of these three different sources to analyse subsidy use over time and across countries. We use the term public aid, state aid and subsidies interchangeably throughout this report.

Growth-driving sectors data

C.16 We use industry-level competition metrics from the State of UK Competition 2024 report for the analysis in Chapter 6. Specifically, we use estimates of business dynamism (entry, exit and job reallocation rates and turnover persistence), cost markups, static competition (Herfindahl–Hirschman Index and concentration ratios), and economic outcomes (R&D expenditure, investment rates and labour productivity).

C.17 The measures in the State of UK Competition 2024 report come from the CMA Microeconomics Unit's analysis of the following microdata sources:

- The Annual Respondents Database X and the Annual Business Survey;
- The Business Structure Database;
- The Longitudinal Business Database;
- The Business Expenditure on Research and Development.

The appendix of the State of UK Competition 2024 contains further details about all these metrics and how they are computed.

C.18 Based on the IS green paper, and conversations with experts and stakeholders, we selected the following industries as our growth-driving sector definitions.

Advanced manufacturing

Manufacture of chemicals and chemical products	20
Manufacture of basic pharmaceutical products and pharmaceutical preparations	21
Manufacture of computer, electronic and optical products	26
Manufacture of electrical equipment	27
Manufacture of machinery and equipment nec	28
Manufacture of motor vehicles, trailers and semi-trailers	29
Manufacture of weapons and ammunition	254
Manufacture of railway locomotives and rolling stock	302
Manufacture of air and spacecraft and related machinery	303
Manufacture of military fighting vehicles	304
Manufacture of transport equipment nec	309
Manufacture of medical and dental instruments and supplies	325

Clean energy

Electricity, gas, steam and air conditioning supply	35
Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus	271
Manufacture of batteries and accumulators	272
Research and experimental development on natural sciences and engineering	721
Manufacture of engines and turbines, except aircraft, vehicle and cycle engines	2811
Engineering activities and related technical consultancy	7112
Environmental consulting activities	74901

Creative industries

Publishing activities	58
Motion picture, video and television programme production, sound recording and music publishing activities	59
Programming and broadcasting activities	60
Computer programming, consultancy and related activities	62
Creative, arts and entertainment activities	90
Libraries, archives, museums and other cultural activities	91
Architectural and engineering activities and related technical consultancy	711
Advertising	731

Specialised design activities	741
Photographic activities	742
Defence	
Manufacture of weapons and ammunition	254
Manufacture of military fighting vehicles	304
Defence activities	8422
Digital and technologies	
Publishing activities	58
Motion picture, video and television programme production, sound recording and music publishing activities	59
Programming and broadcasting activities	60
Telecommunications	61
Computer programming, consultancy and related activities	62
Information service activities	63
Other business support service activities nec	8299
Financial Services	
Financial service activities, except insurance and pension funding	64
Insurance, reinsurance and pension funding, except compulsory social security	65
Activities auxiliary to financial services and insurance activities	66
Life Sciences	
Manufacture of basic pharmaceutical products and pharmaceutical preparations	21
Human health activities	86
Manufacture of irradiation, electromedical and electrotherapeutic equipment	266
Manufacture of medical and dental instruments and supplies	325
Research and experimental development on natural sciences and engineering	721
Professional and Business Services	
Legal and accounting activities	69
Activities of head offices; management consultancy activities	70
Architectural and engineering activities; technical testing and analysis	71
Advertising and market research	73
Other professional, scientific and technical activities	74
Rental and leasing activities	77
Employment activities	78
Services to buildings and landscape activities	81
Office administrative, office support and other business support activities	82
Development of building projects	411

Depending on the specific data sources, these definitions might vary as specified in other parts of this appendix and the figure footnotes.

Growth pillars data sources

EUKLEMS and INTANPROD

C.19 We use the EUKLEMS and INTANProd database to compute investment rates in tangible and intangible assets for the period 2000-2020 and for a selection of peer countries (UK, Germany, France, Italy, US). Investment rates are computed as the ratio of Gross Fixed Capital Formation (GFCF) to Gross Value Added (GVA). Both are measured in volume terms, thus removing the effect of any price changes.

C.20 We source data from two modules. The first one collects data on GFCF from countries' national accounts. The sources for UK data are the OECD annual national accounts database integrated with data from the Office for National Statistics (ONS); data sources for EU countries are Eurostat National Accounts (ESA 2010), and for the US the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS). The second module considers new forms of intangible assets not yet accounted for in the traditional accounting framework.

C.21 The EUKLEMS and INTANProd data updates the widely used EUKLEMS productivity database and extends it with new harmonised estimates of intangible investment for thirty-eight industries and total economy aggregates. The additional intangible assets include industrial design, organizational capital, brand and job training.

C.22 The estimation of investment in these assets follows the principles of estimation of software and databases assets in the national accounts. That is, it covers both purchased (from supply-use tables) and own-account components for all these asset types. The own account part is estimated using the sum-of-costs approach, which implies identifying the main occupations engaged in the production of those assets, estimating a proportion of time spent developing these activities, and attaching a value usually through wages paid.

C.23 We also use the EUKLEMS and INTANProd database to compute investment rates for buildings and construction and residential assets specifically.

C.24 EUKLEMS and INTANProd provides us with information on GFCF for the following asset types contained in the national accounts: transport equipment, IT and communications equipment, other machinery and equipment, residential and other buildings and structures, as well as software and databases, R&D and entertainment and artistic originals. EUKLEMS and INTANProd provides us with information on GFCF for the following asset types contained in the national accounts: transport equipment, IT and communications equipment, other machinery and equipment, residential and other buildings and structures, as well as software and databases, R&D and entertainment and artistic originals.

C.25 To provide a breakdown of investment in infrastructure for the public and private sectors, we rely on the industry-level data available (NACE Rev.2). We assume that investment in public sector infrastructure is that of predominantly public sectors O-Q (Public administration, defence, education, human health and social work activities). For the private sector we have the market sector aggregates available in the database. Results are robust to the inclusion or exclusion of the real-estate sector.

ONS Local Indicators

C.26 We use the Explore Subnational Statistics (ESS) local indicators database to obtain estimates of high-growth business numbers and export shares across UK ITL1 regions. High-growth businesses are defined as those with an average growth in employment of greater than 20% per year over a three-year period. Export shares are derived from estimates of the total value of UK exports including trade in both goods and services, and regional population estimates.

OECD

C.27 We draw from OECD sources (that is, the 2025 release of the STAN database) to compute investment rates for the growth pillar sectors. The OECD provides data on GFCF and GVA figures from the latest national accounts, allowing us to obtain more granular detail on investment at the industry level (some three digit-level NACE industries) compared to data available at the EUKLEMS and INTANProd database (which only cover one-digit and two-digit NACE Rev.2 industries).

C.28 We use data for the period 2019- 2022. We undertake a mapping of sectors and compute aggregate investment rates for the best possible approximation to the growth pillar sectors. In the table below we outline the missing sectors in each of the countries. A tick indicates full availability for our baseline sectors.

	France	Germany	Italy	Japan	UK	US
Advanced manufacturing	✓	*Excludes 325*	*Excludes 252, 302_309, 303, 304, 325*	✓	*Excludes 302_309, 304*	*Excludes 252 ,325*
Life sciences	✓	✓	*Excludes 325*	*Excludes 86*	✓	*Excludes 266, 325*
Energy (including clean)	*D*	*D*	*D*	*D*	*D*	*D*
Defence	✓	✓	*n.a.*	✓	*Excludes 304*	*Excludes 252*

Digital	*J*	*J*	*J*	*J*	*J*	*J*
Creative	*Excludes 90t92*	✓	*Excludes 90t92, 58, 59t60*	*n.a.*	✓	*Excludes 90t92*
Finance and insurance	*K*	*K*	*K*	*K*	*K*	*K*
Professional services	✓	✓	Excludes 69, 70, 71, 73, 74	*M-N*	✓	*Excludes 71, 73, 78, 80t82*

C.29 We also have drawn from OECD national accounts database for the econometric analyses. Extracting the individual countries data allows us to source a few more years of data, compared to downloading directly from cross-country databases such as OECD STAN or EUKLEMS. At the time of analysis, we could extract data on output, inputs, and productivity outcomes up to and including the year 2022.

C.30 For R&D statistics we draw from the OECD ANBERD (Analytical Business Enterprise Research and Development database. The dataset contains annual data on R&D expenditures for OECD countries at the industry level (ISIC Rev.4) from the early 90s onwards. The data cover about one hundred manufacturing and service industry groups and mainly comprises business R&D spending. The data are available in national currencies as well as in US dollars at Purchasing Power Parity (PPP), both at current and constant prices.

C.31 The OECD is also our data source for measuring innovation, and trade in goods and services. The OECD compiles information on patents for selected technologies (environment related technologies, AI, biotech, medical, nanotech, pharmaceuticals, and ICT). Information is provided on both patent applications and grants, and includes those registered at the European Patent Office, WIPO and the US patent office. We extract information from the OECD on exports in goods and services, and compute as a share of GDP for selected countries.

Other industry-level data sources

C.32 The Competitiveness Research Network dataset (CompNet) is a micro-aggregated dataset of indicators of competitiveness and productivity for twenty European countries.[7] The indicators are computed at the firm level using data from national data providers and then aggregated and harmonised to allow cross-country comparisons.

C.33 The ONS firm-level profit margins, intermediate consumption markups and labour markups from the Annual Business Survey (December 2024 release) provides publicly available estimates obtained from the microdata in the Annual Business Survey. Estimates are available for the whole-economy, broad sectors (for instance, construction, services, etc…), SIC sections and two-digit industries for the period 1997-2022. We use these estimates when our State of the UK Competition report measures were not available for some industries of interest.

C.34 The ONS industry deflators dataset provides industry deflators from 1997 to 2023 on a monthly, quarterly and annual basis, with 2019 as reference year. The deflators provided are produced by aggregating product level deflators for each industry. The deflators cover mostly whole two-digit SIC industries, with a small proportion of further disaggregated industries (for instance, industry 3315, 3316 and 33OTHER, or 351 and 352-353). In these cases, the disaggregation exactly covers all the three- or four-digit industries in a two-digit code, making possible to compute the two-digit deflator as an average of all the subcodes' ones.

C.35 The ONS National Online Manpower Information System (NOMIS) provides statistics related to population, society and the labour market at national, regional and local levels. We use counts of the number of enterprises within a geographic area, down to Middle Layer Super Output Areas (MSOAs), broken down by employment size band, detailed industry, and legal status. Firm counts are sourced from the Inter-Departmental Business Register (IDBR). Total firm counts in 2024 for all enterprises by NUTS3 (2013) geographic areas by five-, four-, three- and two-digit SIC2007 industry classifications are utilised within this analysis.

C.36 Glass.AI uses machine learning tools to extract information on firms from many business websites, news outlets, social media, and official sources. Based on this information, Glass.AI has computed estimates of regional location quotients for each of the eight industrial strategy sectors.

---

[7] CompNet asks users to be aware that small differences in data collection rules and procedures across countries may exist and are out of its control. Nevertheless, comparability issues appear to be limited.

D. Methodology

Industrial policy counts from GTA

D.1 The filtered version of the Global Trade Alert (GTA), provided by Juhász, Lane, Oehlsen and Pérez, only contained a classification of products affected by each measure but not of the industries. We therefore merged the filtered dataset to an unfiltered GTA dataset that we downloaded in December 2024. In doing so, we have treated the filtered version as the baseline, therefore only keeping observations that were originally included in the filtered version of the dataset.

D.2 The GTA classifies industries based on the Central Product Classification (CPC). We translated this classification into the Standard Industrial Classification (SIC 2007), used throughout the report, thanks to the correspondence tables provided by the United Nations Statistic Division (UNSTAT). Three steps were necessary:

- Map CPC v.2 codes into the International Standard Industry Classification revision 4 (ISIC Rev. 4);
- Then map from ISIC Rev. 4 into NACE Rev. 2 (Nomenclature statistique des activités économiques dans la Communauté europééennecodes);
- And finally, map from NACE Rev. 2 to SIC 2007.

D.3 We have taken care not to double count measures whenever multiple industries in one classification translated into one industry in another classification (for instance, CPC codes from 01111 to 01190 all correspond to ISIC Rev. 4 code 0111. A GTA measure affecting industries 01111 and 01112 would only count once, not twice when translating to ISIC Rev. 4 industry 0111).

D.4 For the descriptive statistics we adopt the suggestion in Juhász, Lane, Oehlsen and Pérez' update to their paper to restrict the data to those observations announced in the same year they are added to the dataset. This is done to account for the fact that the GTA is a continuously updated database, therefore as time passes, earlier years receive a more complete inventory of policies. In the regressions, we instead use all available observations.

D.5 Some observations in the dataset are implemented by supranational entities (for instance, the European Union or the African Development Bank Group) or by multiple countries together (for instance, Belgium, Hungary, Poland and Spain). In these cases, we have not allocated the measure to each country, but classified it as implemented by multiple countries and excluded it from the analysis.

Industrial policy expenditure from QuIS

D.6 The QuIS data is made up of two datasets – one on financial instruments and one on tax and grant expenditures. We combine the two datasets. As a result, in each year there can be more than one type of industrial policy.

D.7 For our regression analysis we aggregate the industrial policy spending data to the SIC section level, for each country. For some countries there may be years when we do not observe any industrial policies. In these cases, we assume that there was no industrial policy spending in that particular year.

D.8 There are two distinct variables included in the QuIS. One contains the raw spending in the national currency, and another is measured as a percentage of national GDP. We use the percentage of GDP variable in our analysis.

Subsidies

D.1 Subsidies can take many forms, such as grants, tax advantages or loans. For the analysis of subsidies in this report, we do not distinguish between these different forms and treat all entries in the different subsidy databases the same. This broadly aligns with the definition of a subsidy under section 2 of the UK's Subsidy Control Act 2022 as an instance of a public authority conferring an economic advantage onto one or more enterprises (whether directly or indirectly) from public resources.

D.2 We clean the UK, EU and Spanish subsidy databases in the following way. We remove observations with obviously erroneous subsidy dates (less than 0.01% of total observations). We remove all subsidies with a subsidy award status indicating that they have been rejected or deleted (less than 0.01% of total observations). We remove all subsidies issued by public authorities to firms based outside the issuing country. In the case of the UK database this includes subsidies in Gibraltar or Calais in France (less than 0.01% of total observations). We exclude all subsidies which only provide the subsidy value as a range, instead of an exact monetary value (4% of total observations). We also remove observations with obviously erroneous firm size classifications (less than 0.01% of total observations).

D.3 We separate out a small number of subsidies given for very specific reasons. We identify COVID-19-related subsidies as those explicitly defined as such in the database. We identify one exceptionally large subsidy of £22 billion provided for the capitalisation of the former UK Infrastructure bank (79% of total subsidy value in 2022). Both special cases are excluded from our baseline analysis.

D.4 Additionally, we identify the UK's Department for Energy Security and Net Zero's (DESNZ) Contracts for Difference (CfD) subsidy scheme. These awards are exceptionally large and applied over a 15-year horizon. DESNZ's provides estimates of scheme costs and acknowledge that they "cannot be predicted accurately in advance as it is dependent on several uncertain factors including future wholesale prices and how much electricity each project generates". Therefore, we exclude CfD awards in all subsidy analysis of the UK but include them in international comparisons to ensure comparability with other European nations that use similar schemes.

D.5 For regional subsidy analysis, we exclude all observations registered at a national level, to multiple regions or to no geography, as they cannot be accurately allocated to a specific ITL code. The regional analysis also excludes all subsidies issued by public authorities of the Isle of Man and Channel Islands. All regional analysis is reproduced excluding subsidy awards with a value greater than £100 million to account for the impact of outliers. Similarly, all analysis disaggregated by firm size excludes observations that are missing their size classification. In total, we exclude 6% of observations.

D.6 We convert all subsidy values denominated in non-euro currencies to euros using European Central Bank (ECB) average yearly exchange rates. All euro denominated subsidy values are then converted to pound sterling using ONS average yearly exchange rates. Figure footnotes detail any additional assumptions that were made to produce the analysis.

Shift-share regressions

D.7 The shift element of the shift-share explanatory variable uses national level counts of new industrial policy interventions, from 2010-2022 (Psi_t), for several European nations. The data is obtained from Juhász, Lane, Oehlsen and Pérez' classification of GTA data, which measures the introduction of new additional industrial policies.

D.8 The shares are based upon the 2010 NACE Rev. 2 industry by NUTS2 region employment level data extracted from the European Structural Business Statistics (SBS). As the SBS dataset contains employment level data for certain regions under different iterations of NUTS codes (such as 2013, 2016 and 2021 classifications), we convert all regional employment level data to NUTS 2021 codes.

D.9 In most instances (>95% regions) this required no adjustment of employment level data, only administrative codes. In instances of two or more regions merging into a single region, the sum of the employment level data was used. In the instances where a NUTS region(s) was split into multiple regions the industry employment levels were apportioned to each sub-region based upon their respective 2010 population shares. We calculated population shares using European Commission conversion matrices.

D.10 The resulting 2010 industry employment shares within a given region all sum to one and are used as lagged employment shares ($Beta_{its}$). The country level shifts are interacted with the employment shares and aggregated across industries to yield the regional shift-share explanatory variable, $Theta_{it}$, as detailed in equation (1).

$$(1) \quad \theta_{it} = \sum_{s} \beta_{its} \cdot \psi t$$

D.11 We take the average of the regional shift-shares over time to compute our industrial policy exposure (instrument measure). Our baseline regressions utilise GVA and employment (hours worked) by NUTS2 regions data from Eurostat and the ONS. Labour productivity - calculated as the ratio of GVA to hours worked - and employment are specified as dependent variables with multiple leads and lags. The shift/share explanatory variable, alongside year and region fixed effects, estimates the effect of regional exposure to industrial policy on the outcomes.

Location quotients

D.12 We calculated location quotients derived from NOMIS data as the ratio of regional establishment concentration over national concentration. Regional concentration is the ratio of the total number of firms operating in a sector (in a region) over the total firm count (in the same region) across all sectors.

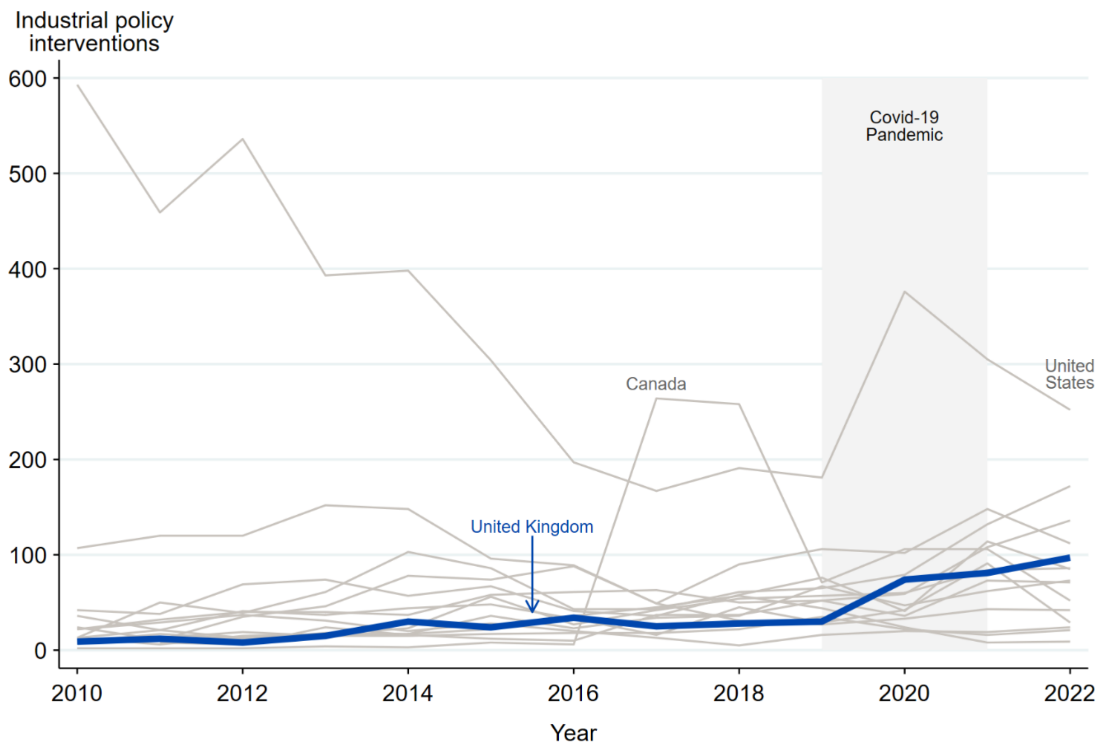
D.13 National concentration is the ratio of the total number of firms operating in each sector across all regions, over the total firm count across all sectors, across all regions.

D.14 Glass.AI location quotients were provided, pre-calculated, according to the same methodology. The choropleth map outputs display those ITL3 regions with location quotient values that fall within the top 25% (>75th percentile) of the distribution. Therefore, the coloured areas are those 25% of areas with the highest concentration of firms in each industry relative to the national average concentration in that industry.

E. Additional figures

Figure E.1: The use of industrial policies has increased around the world

New industrial policies, for fifteen countries, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database. All policies included, regardless of year of publication



Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. The graph includes the 15 countries with the highest number of IP in the period 2010-2022. The other countries included are Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Poland, Russia, Saudi Arabia, Spain, and US. Source: *Global Trade Alert* (2010-2022).

Figure E.2:Among the industries that receive industrial policies, there are no prevalent combinations of industrial policy categories

Clustering (hierarchical clustering dendrogram) based on QuIS (2019-2022) data on different industrial policy category spending in each industry

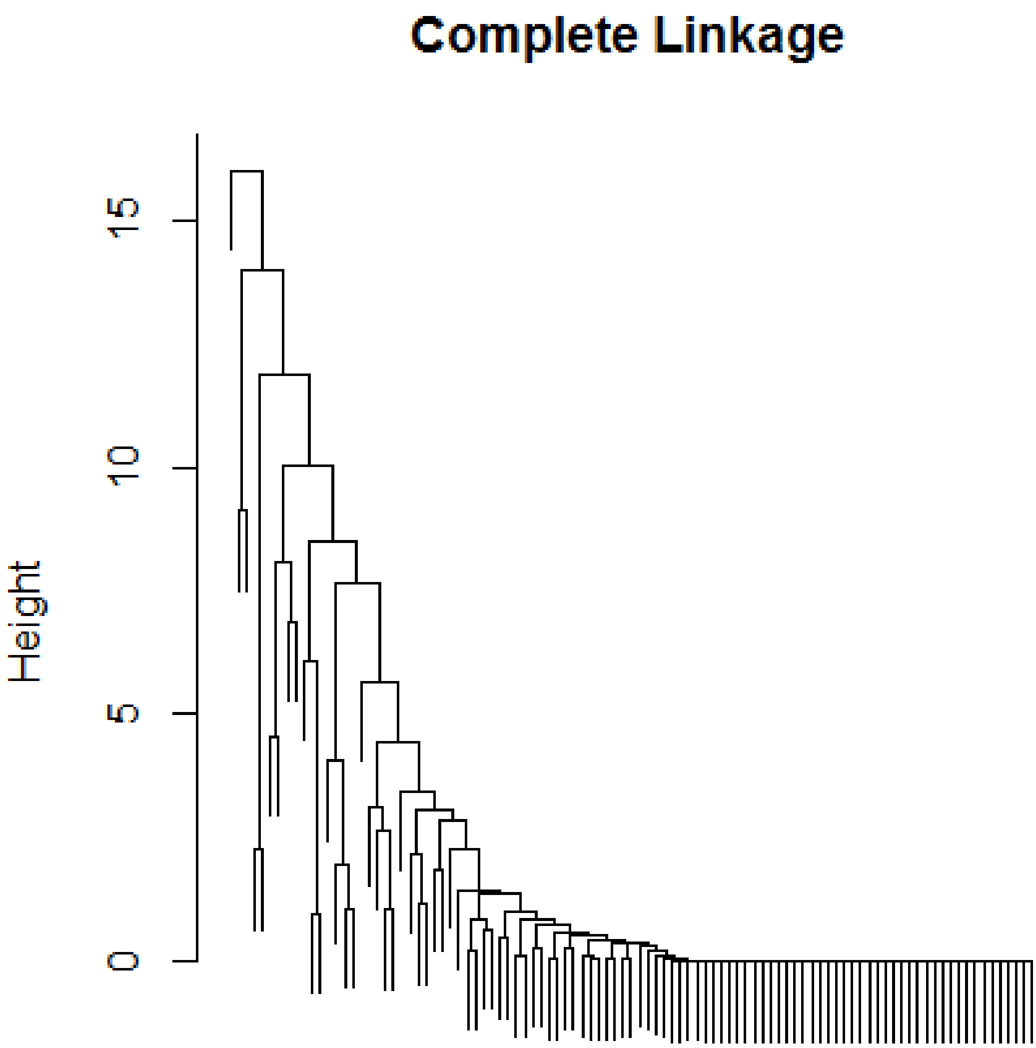
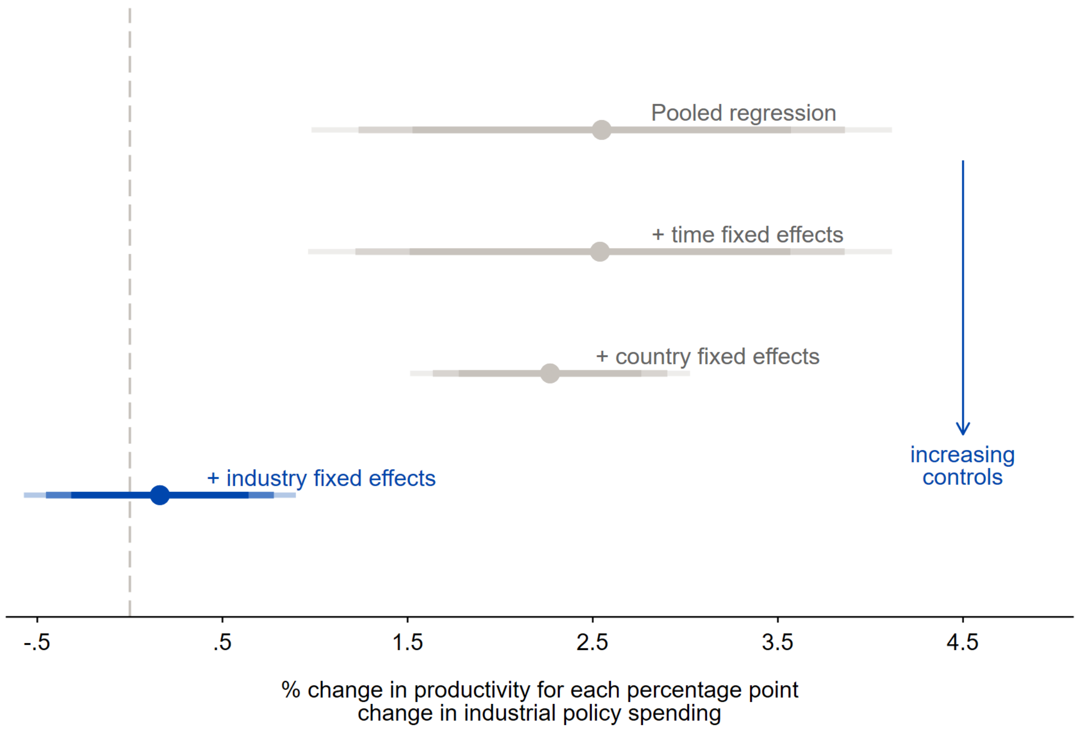


Figure E.3: Industrial policies tend to target more productive industries, where they can have small positive effects

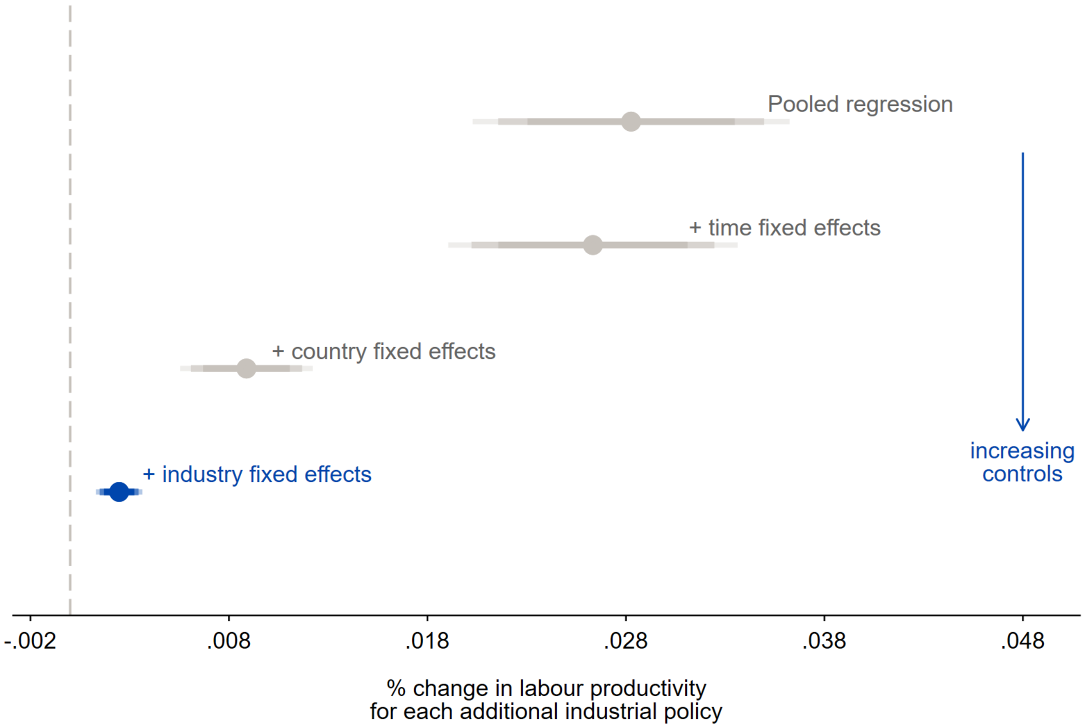
Coefficients from regressions of labour productivity on industrial policy spending, 2019-2022, from the OECD national accounts database



Standard errors clustered by country and industry. Labour productivity defined as Gross Value Added divided by amount of hours worked. Included countries: Canada, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Sources: *OECD* (2019-2022) and *Quantifying Industrial Strategies* (2019-2022).

Figure E.4: Industrial policies tend to be more concentrated on more productive industries, where they can have small positive effects

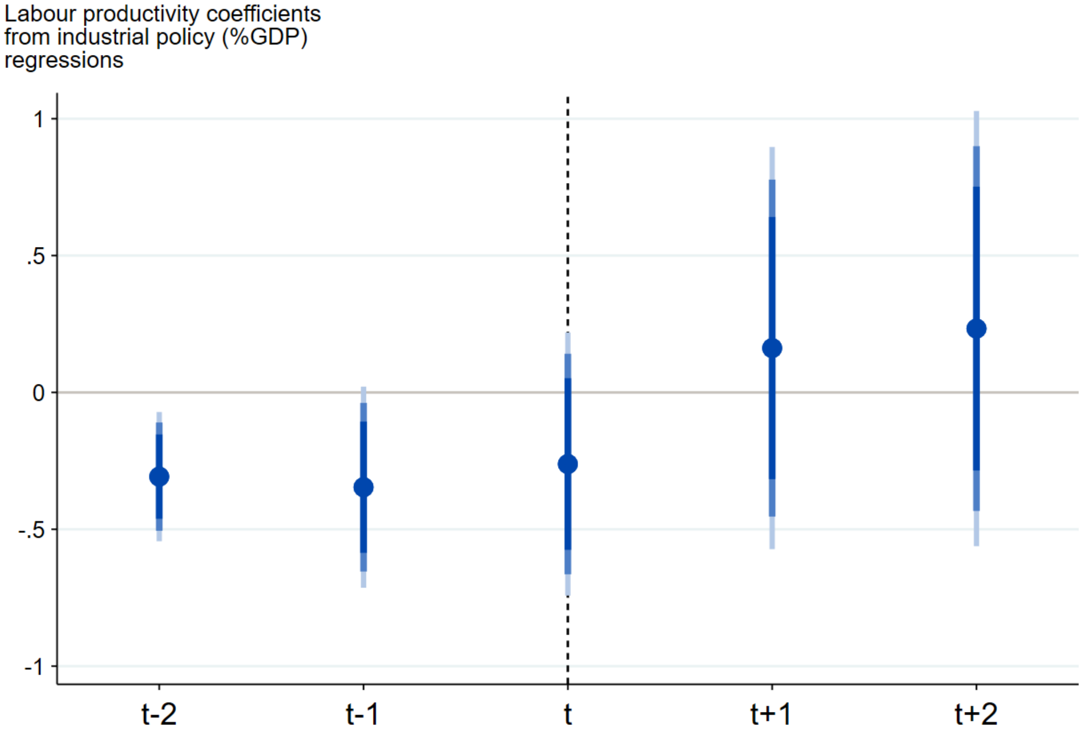
Coefficients from regressions of labour productivity on industrial policy spending, 2010-2022, from the OECD national accounts database



Robust standard errors. Labour productivity defined as Gross Value Added divided by amount of hours worked. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Sources: *Global Trade Alert* (2010-2022) and *OECD* (2019-2022).

Figure E.5: Industrial policy spending is followed by small productivity increases

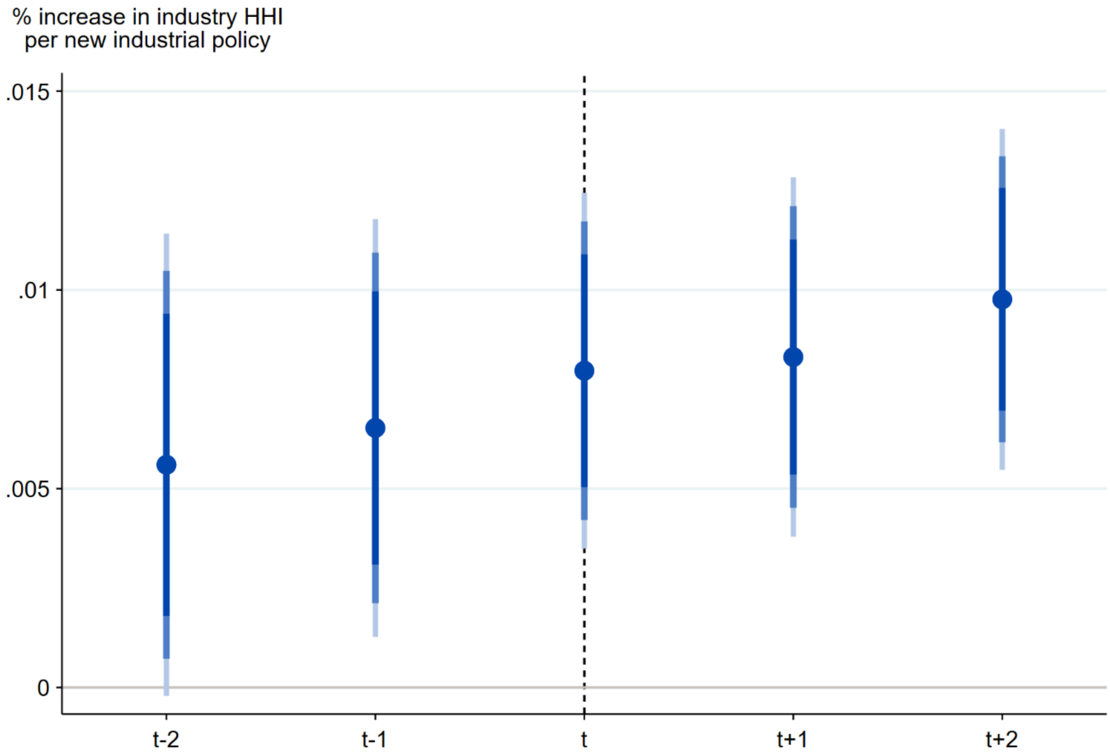
Coefficients from regressions of labour productivity on industrial policy spending, 2019-2022, from the OECD national accounts database



Time, country and industry fixed effects included, standard errors clustered by country and industry. Labour productivity defined as Gross Value Added divided by amount of hours worked. Included countries: Canada, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Sources: *OECD* (2019-2022) and *Quantifying Industrial Strategies* (2019-2022).

Figure E.6: There is no clear effect of industrial policy counts on concentration

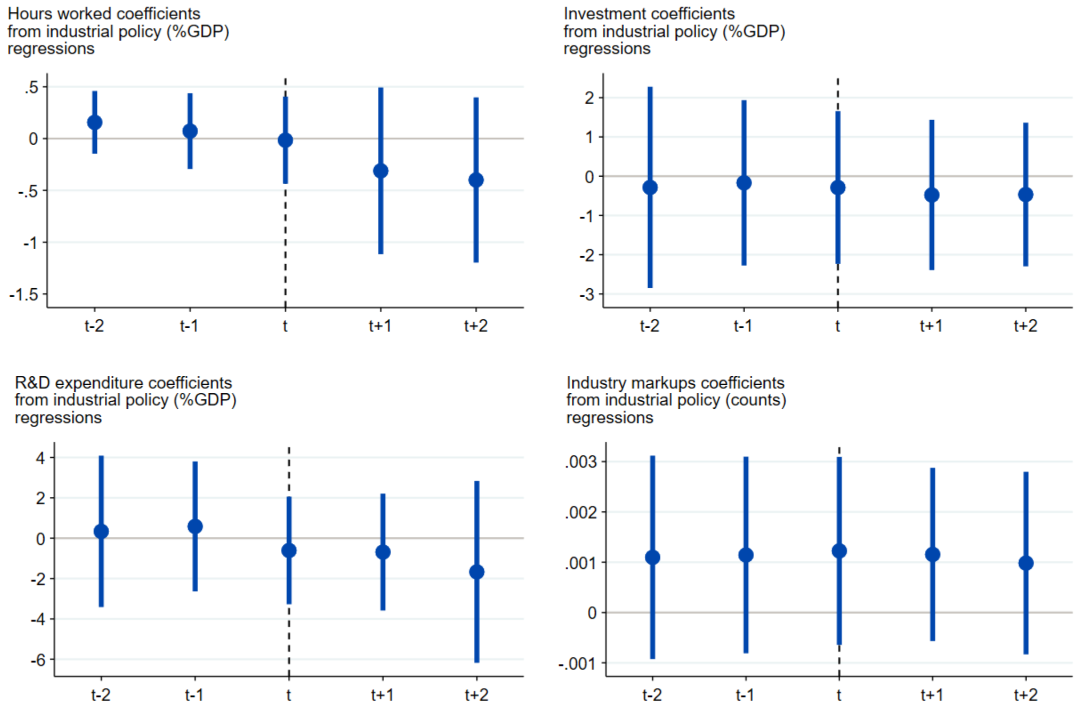
Coefficients from regressions of HHIs on industrial policy counts, 2010-2022, CompNet



Time, country and industry fixed effects included, robust standard errors. Herfindahl–Hirschman Index (HHI) is computed at 2-digit NACE level. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Latvia, Lithuania, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the UK. Sources: *CompNet database* (1997-2021) and *Global Trade Alert* (2010-2022).

Figure E.7: There is no clear effect of industrial policy on employment, investment, R&D or markups

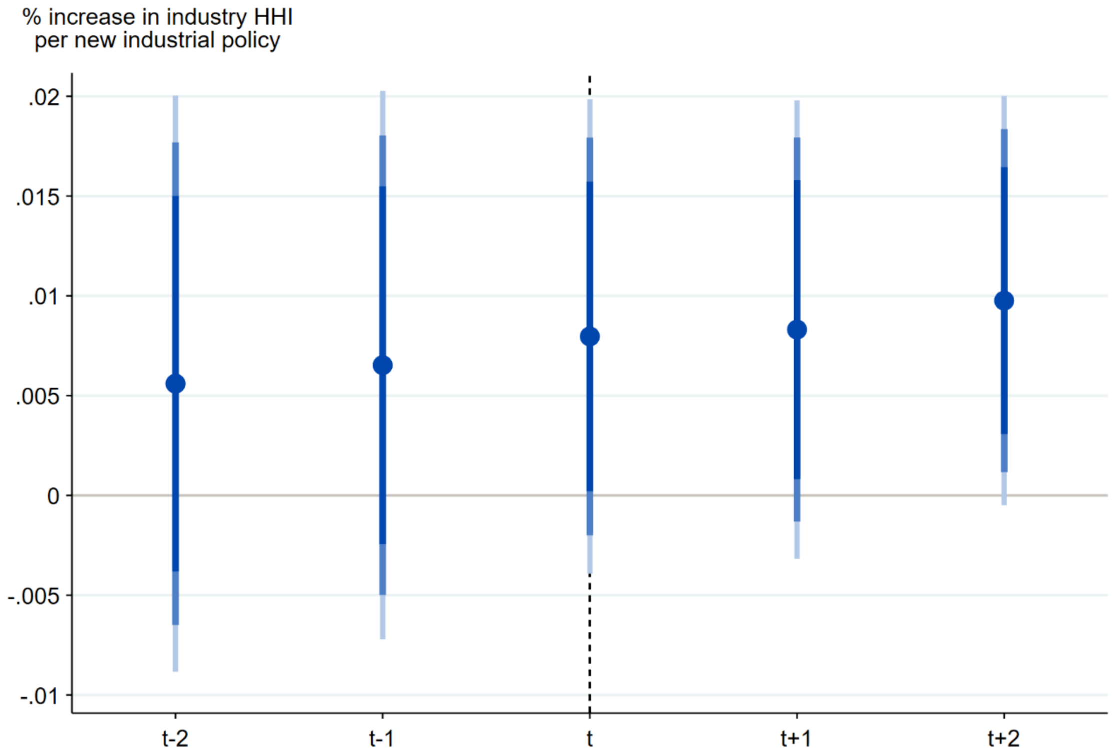
Coefficients from regressions of (1) hours worked, (2) investment, (3) R&D and (4) markups on industrial policy spending, 2019-2022, from the OECD national accounts database and CompNet, 2010-2022



Time, country and industry fixed effects included, standard errors clustered by country and industry. For panels 1-3 we use industrial strategy data from *Quantifying Industrial Strategies* (2019-2022). Included countries: Canada, Denmark, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Hours worked, investment and R&D data are from *OECD* (2019-2022). Panel 4 uses industrial policies counts as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data (2010-2022). Included countries: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Latvia, Lithuania, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the UK. Markup from *CompNet database* (1997-2021) and is estimated using the production function approach (Ordinary Least Square estimation of a translog production function, with materials as flexible input). Top and bottom 1% markups in each year have been excluded.

Figure E.8: There is no clear effect of industrial policy counts on concentration

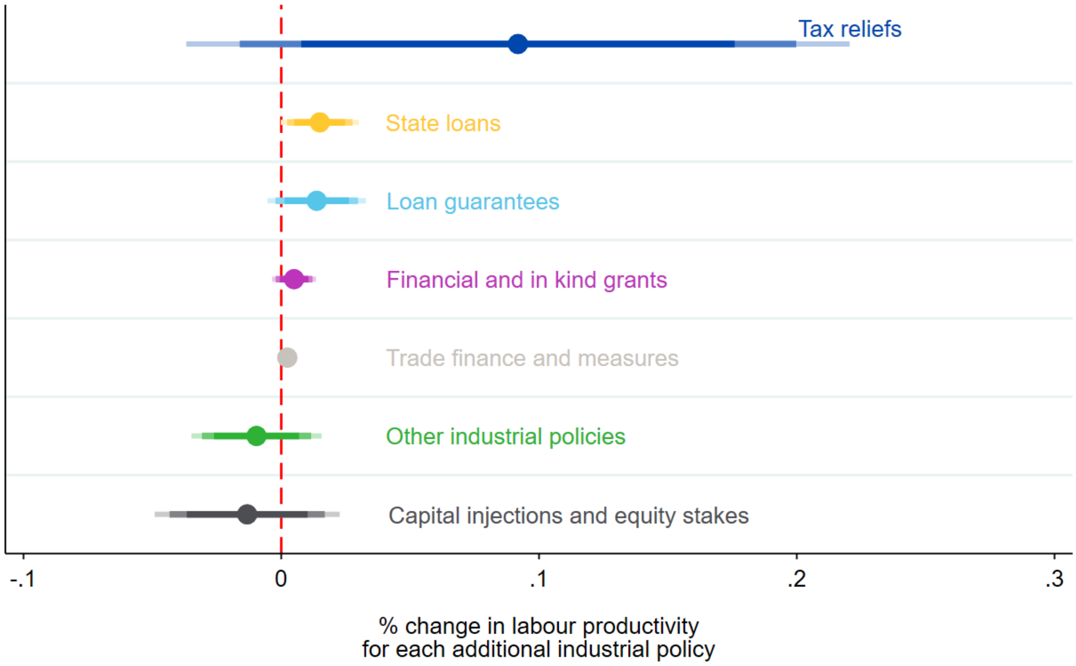
Coefficients from regressions of HHIs on industrial policy spending, 2010-2022, from CompNet



Time, country and industry fixed effects included, standard errors clustered by country and industry. Herfindahl–Hirschman Index (HHI) is computed at 2-digit NACE level. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Latvia, Lithuania, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the UK. Sources: *CompNet database* (1997-2021) and *Global Trade Alert* (2010-2022).

Figure E.9: Tax credits appear to be associated with the largest productivity increase

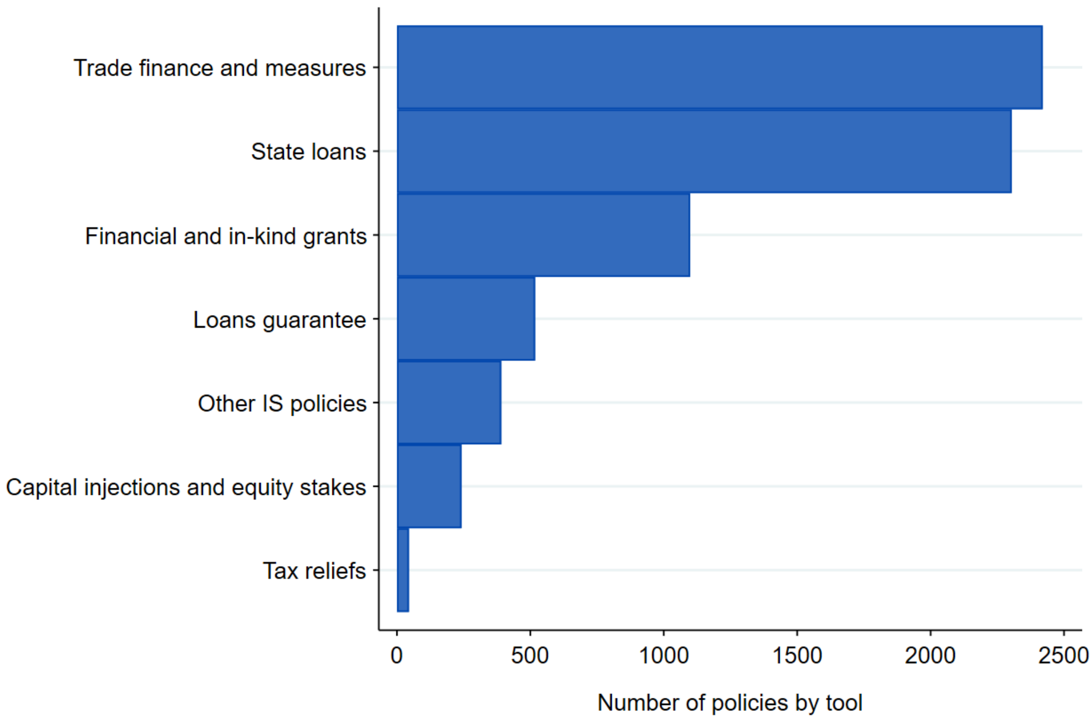
Coefficients from regressions of labour productivity on industrial policy counts, by instrument type, 2019-2022, from the OECD national accounts database



Time, country and industry fixed effects included, standard errors clustered by country and industry. GTA instrument category coefficients from separate regressions. Labour productivity defined as Gross Value Added divided by amount of hours worked. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Sources: *Global Trade Alert* data (2010-2022) and *OECD* (2010-2022)

Figure E.10: The GTA database contains a relatively small number of tax relief measures, compared to other industrial policy instruments

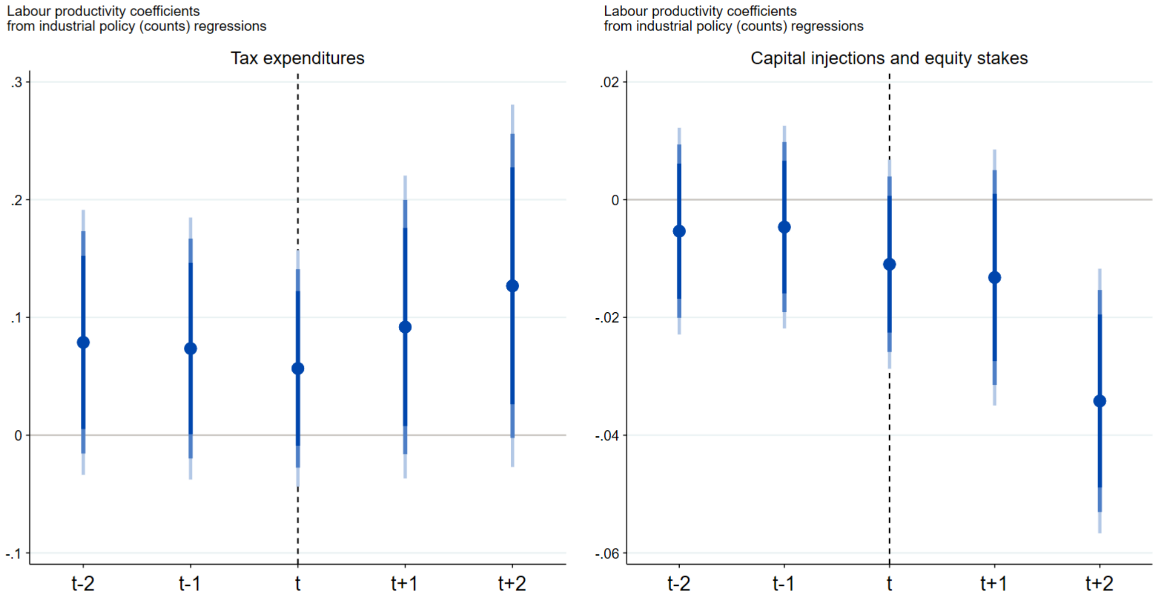
Number of policies by instrument type, 2010-2022, from Global Trade Alert database



Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Source: *Global Trade Alert* data (2010-2022).

Figure E.11: There are substantial selection effects, but different tools are associated with different post-introduction productivity changes

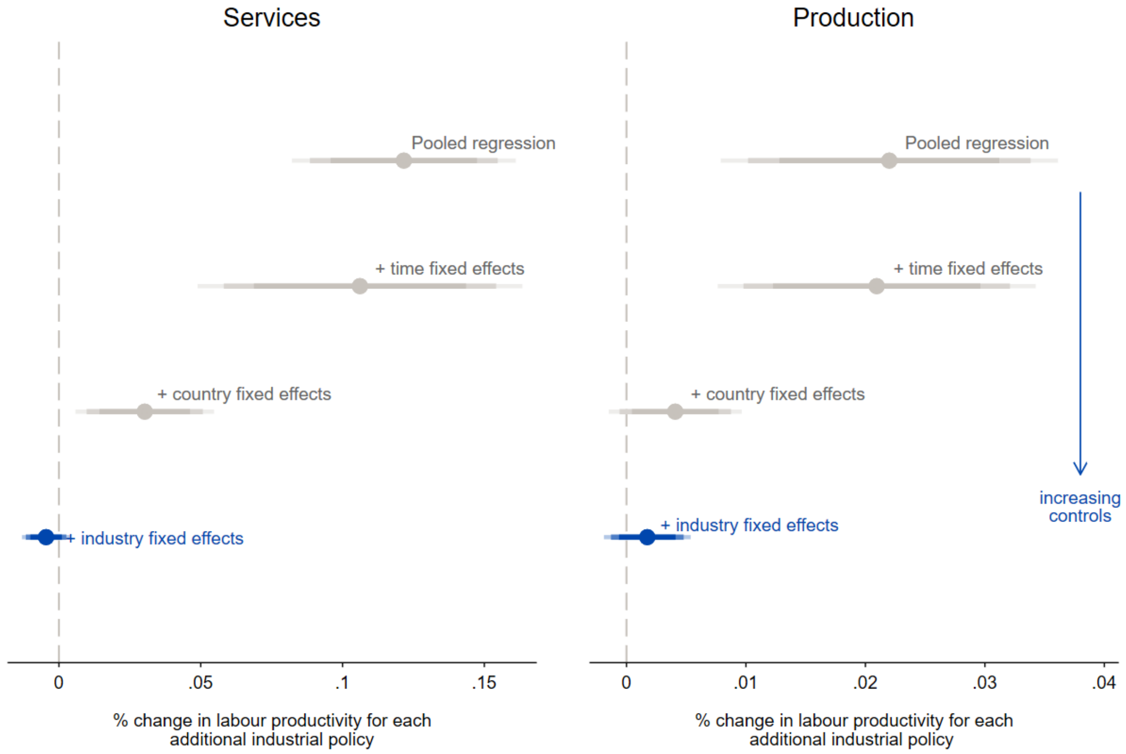
Coefficients from regressions of labour productivity on a) tax expenditure and b) capital injections and equity stakes policy counts, 2019-2022, from the OECD national accounts database, 2010-2022



Time, country and industry fixed effects included, robust standard errors. Labour productivity defined as Gross Value Added divided by the amount of hours worked. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland,France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Sources: *Global Trade Alert* data (2010-2022) and *OECD* (2010-2022)

Figure E.12: Industrial policies are positively related to productivity in production but not in services

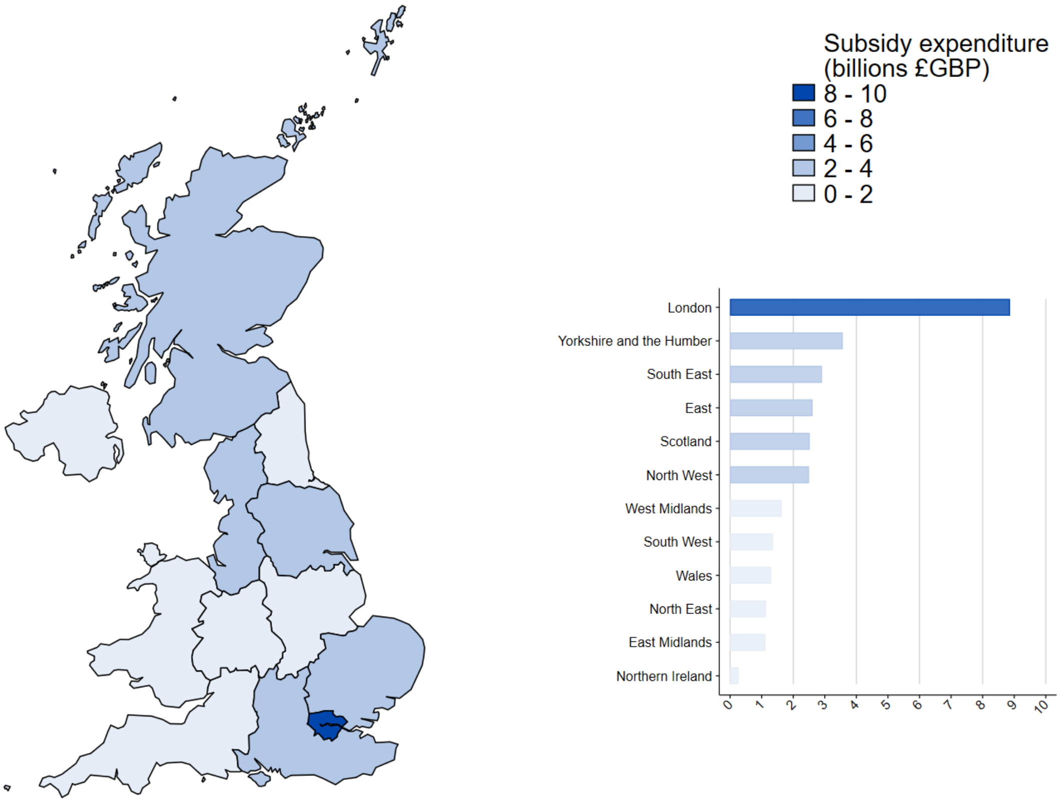
Coefficients from regressions of labour productivity on industrial policy counts, for services and production, 2019-2022, from the OECD national accounts database



Standard errors clustered by country and industry. Labour productivity defined as Gross Value Added divided by amount of hours worked. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to *Global Trade Alert* data. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Sources: *Global Trade Alert* (2010-2022) and *OECD* (2010-2022).

Figure E.13: Total subsidy expenditure is largest in London

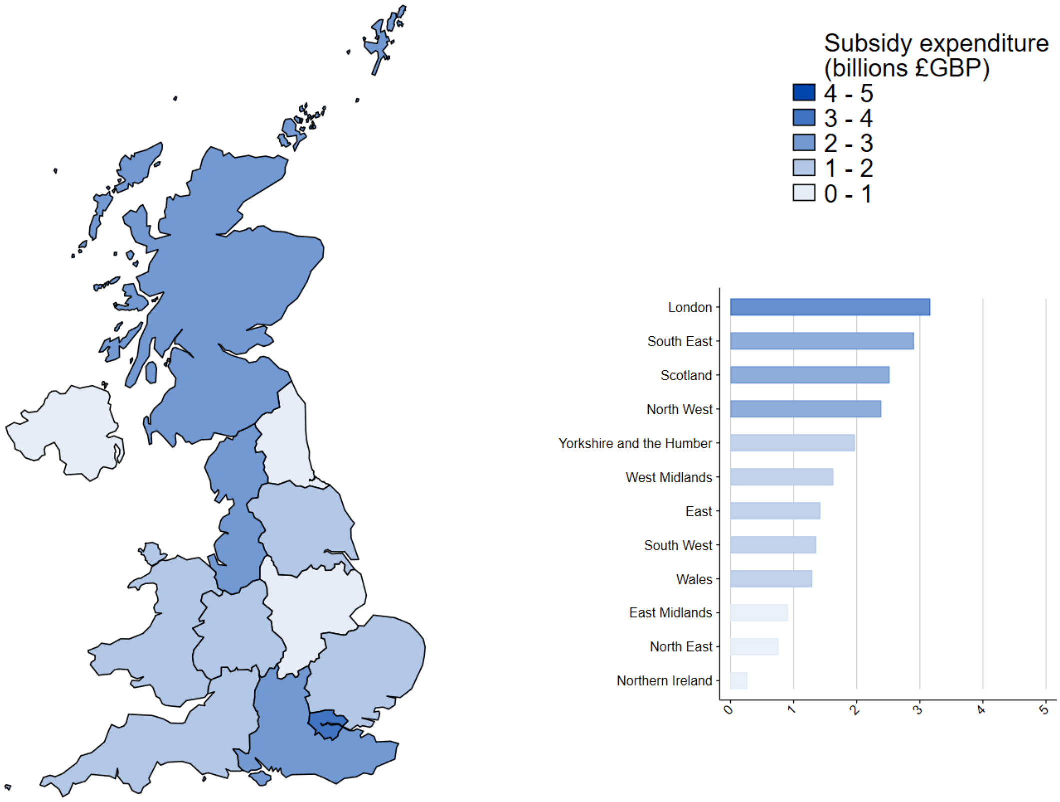
Subsidies across ITL1 regions, UK, 2021-2023, from the EU State Aid and UK Subsidy database and ONS regional accounts



UK regions' subsidy expenditure (2021-2023). Subsidies provided for capitalisation of the UK Infrastructure Bank and Contract for Difference awards are excluded. Sources: *EU State Aid Database* (2021-2023); *UK Subsidy Database* (2021-2023).

Figure E.14: Excluding the largest subsidies, London and the South East receive the largest amounts

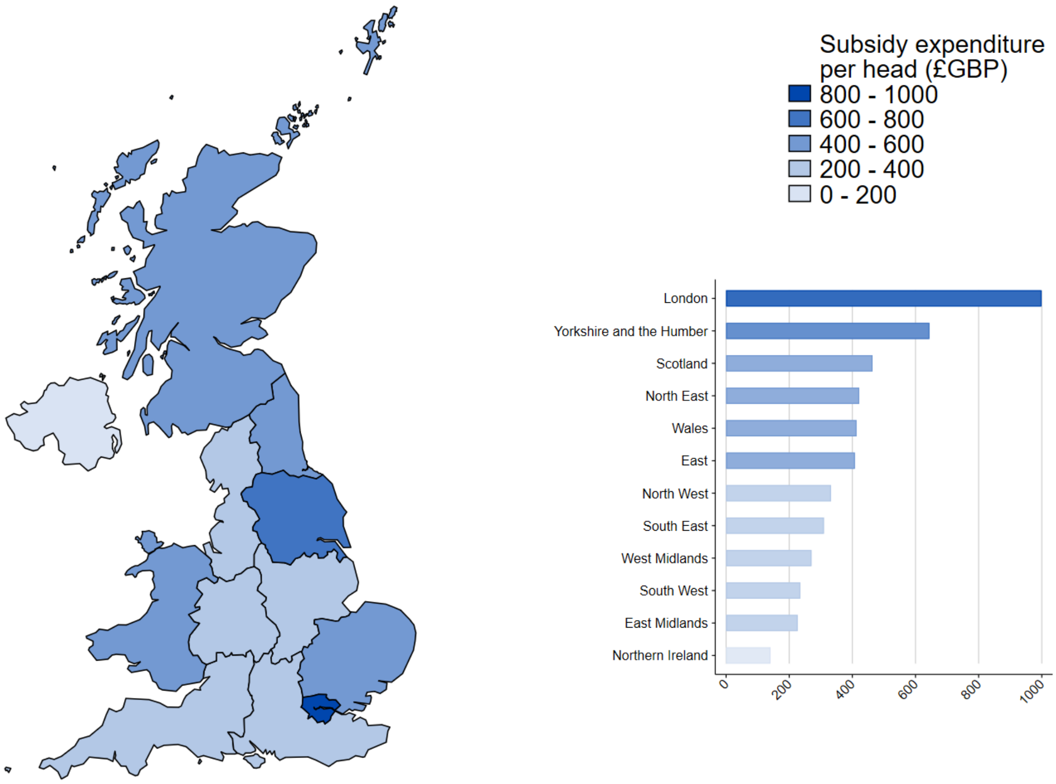
Subsidies across ITL1 regions excluding those awards over £100 million, UK, 2021-2023, from the EU State Aid and UK Subsidy database and ONS regional accounts



UK regions' subsidy expenditure (2021-2023). Analysis excludes all subsidy awards with a value greater than £100 million GBP. Sources: *EU State Aid Database* (2021-2023); *UK Subsidy Database* (2021-2023).

Figure E.15: Per capita, subsidies are largest in London and Yorkshire and the Humber

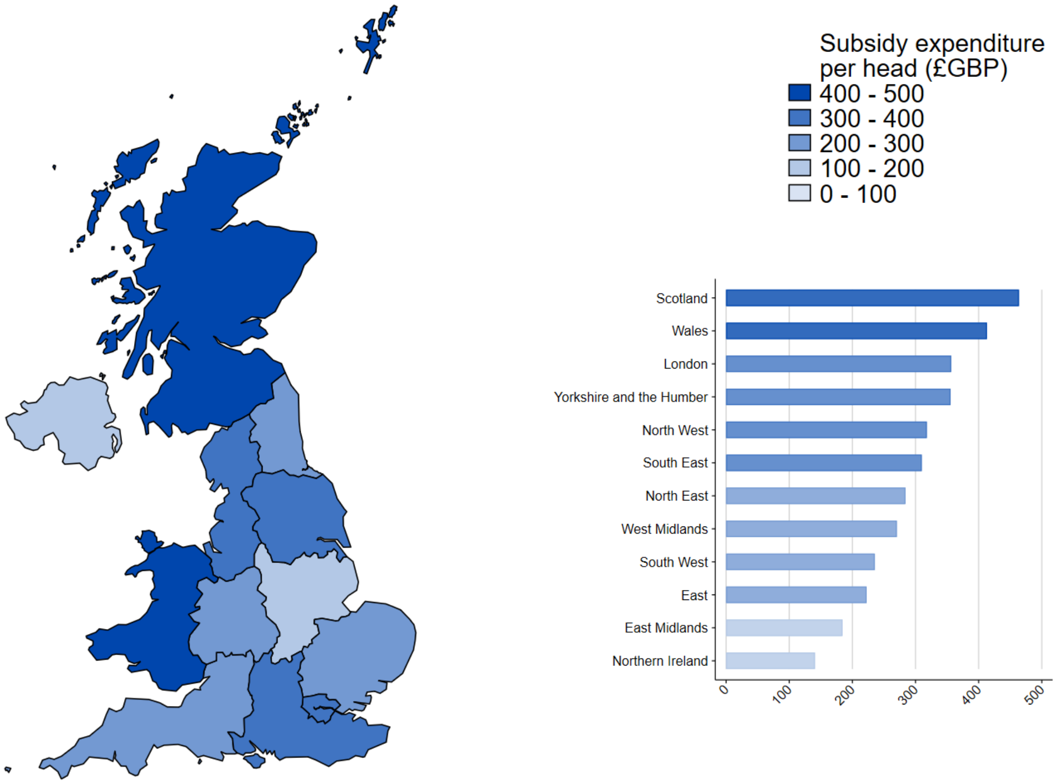
Subsidies per capita across ITL1 regions, UK, 2021-2023, from the EU State Aid and UK Subsidy database and ONS regional accounts



UK regions' average subsidy expenditure per head (2021-2023). Subsidies provided for capitalisation of the UK Infrastructure Bank and Contracts for Difference awards are excluded. Scotland and Northern Ireland population data covers the period 2021-2022. Sources: *EU State Aid Database* (2021-2023); *UK Subsidy Database* (2021-2023); *NOMIS Population Estimates* (2021-2023).

Figure E.16: Excluding the largest subsidies, per-capita subsidies are largest in Scotland and Wales

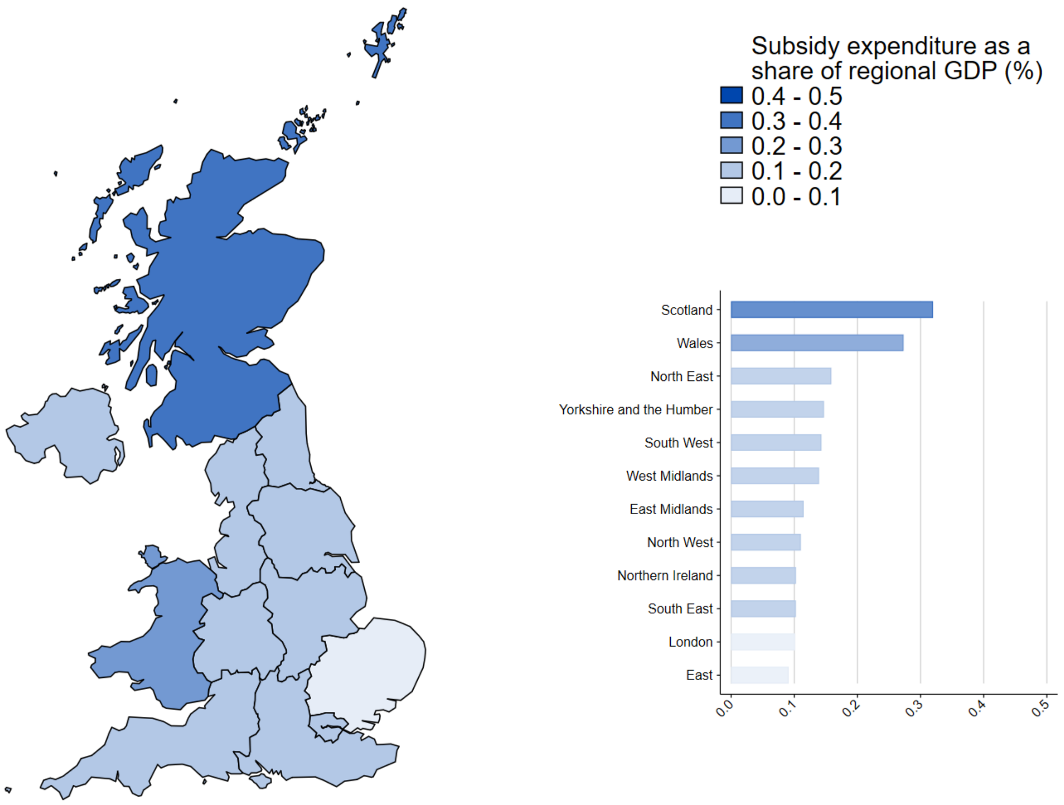
Subsidies per capita across ITL1 regions excluding those awards over £100 million, UK, 2021-2023, from the EU State Aid and UK Subsidy database and ONS regional accounts



UK regions' average subsidy expenditure per head (2021-2023). Analysis excludes all subsidy awards with a value greater than £100 million GBP. Scotland and Northern Ireland population data covers the period 2021-2022. Sources: *EU State Aid Database* (2021-2023); *UK Subsidy Database* (2021-2023); *NOMIS Population Estimates* (2021-2023).

Figure E.17: Scotland and Wales have received a higher share of subsidies, once we exclude subsidies over £100 million

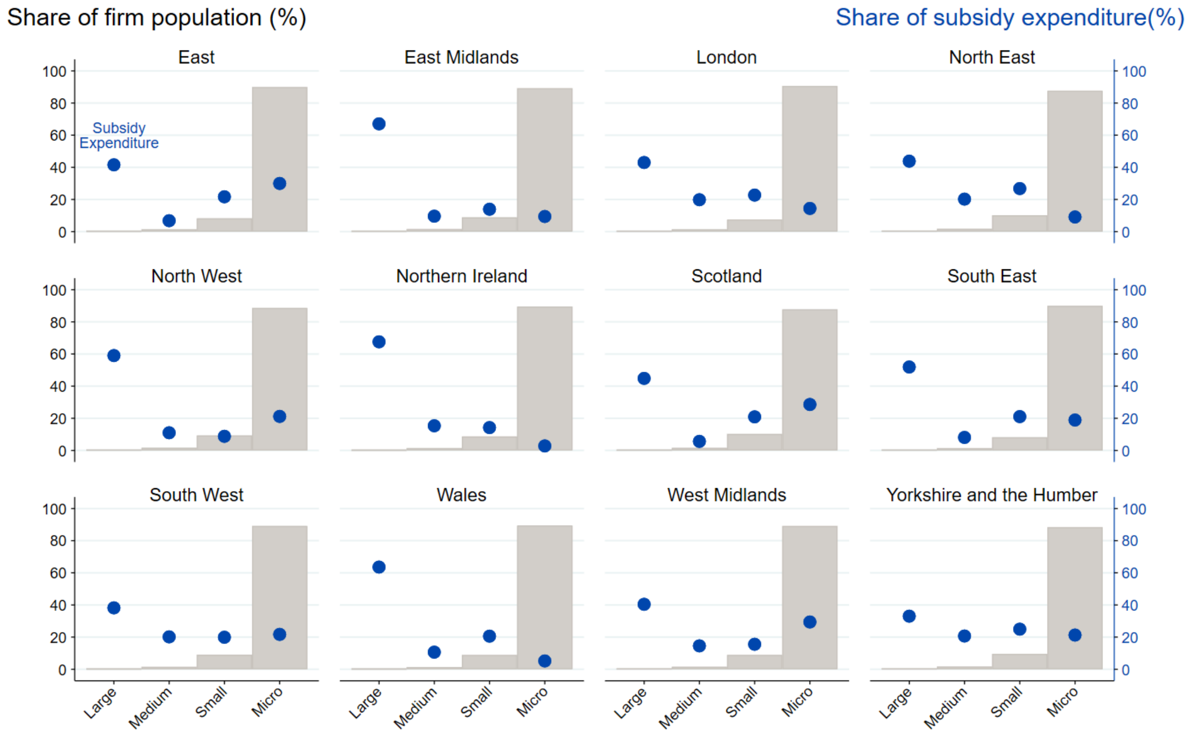
Subsidies as a share of regional GDP excluding those awards over £100 million, UK, 2021-2022, from the EU State Aid and UK Subsidy database and ONS regional accounts



UK regions' average subsidy expenditure as a share of GDP (2021-2022). Analysis excludes all subsidy awards with a value greater than £100 million GBP. Sources: *EU State Aid Database* (2021-2022); *UK Subsidy Database* (2021-2022); *ONS Regional Accounts* (2021-2022).

Figure E.18: In all regions subsidies tend to go mostly to large firms when we exclude subsidies over £100 million

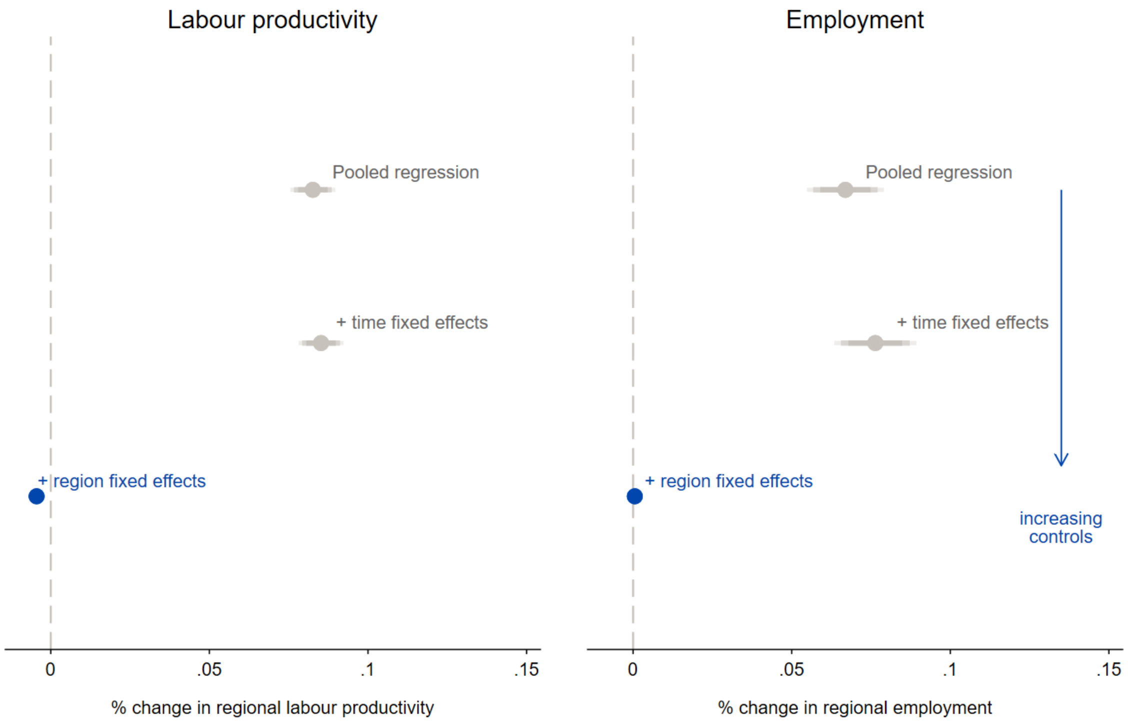
Firm size distribution and subsidy distribution excluding those awards over £100 million, by UK region, 2021-2023, from the UK Subsidy database and ONS business data



Share of business population and subsidy expenditure (2021-2023) disaggregated by firm size (employment sizebands) across UK ITL1 regions. Analysis excludes all subsidy awards with a value greater than £100 million GBP and COVID-19 support subsidies. Sources: *ONS Business Workbooks* (2021-2023); *UK Subsidy Database* (2021-2023).

Figure E.19: Industrial policies tend to go to more productive regions

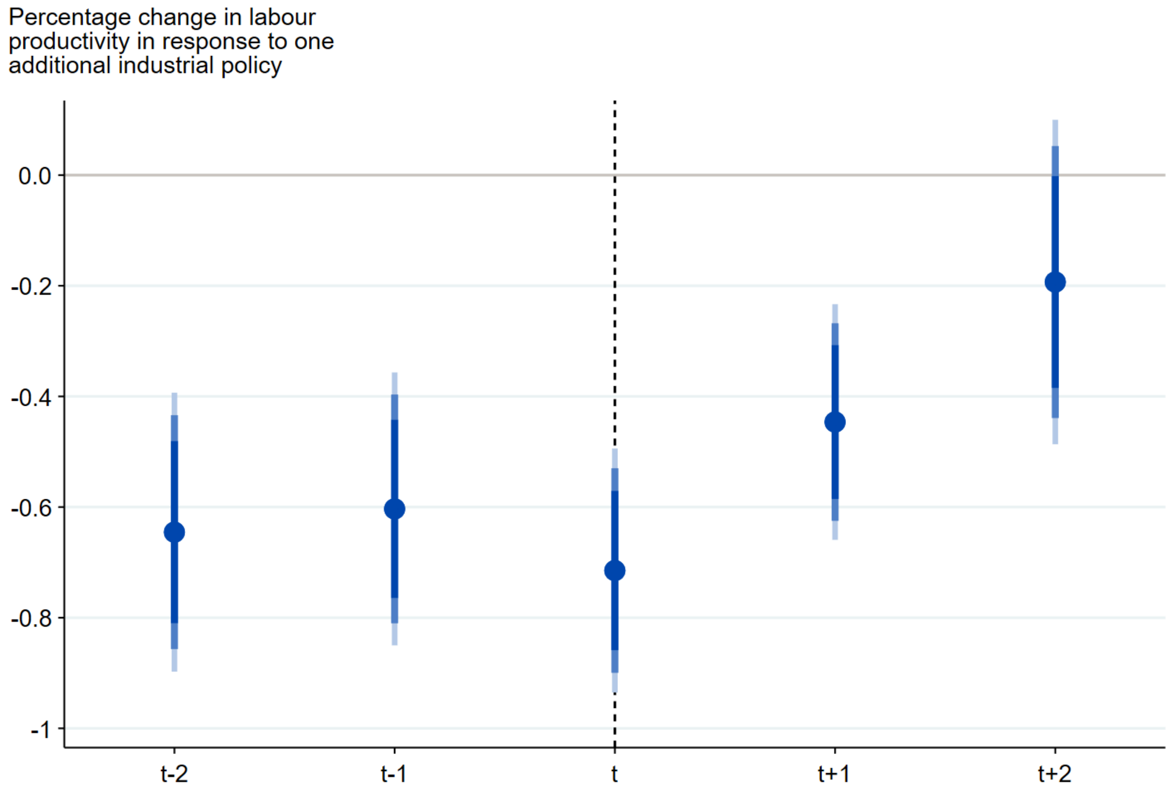
Coefficients from regressions of a) labour productivity and b) employment (hours worked) on industrial policy exposure, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, Eurostat and ONS data



Robust standard errors. Labour productivity defined as Gross Value Added (GVA) divided by employment. Employment reflects hours worked data from *EUROSTAT and ONS* (2010-2022). Industrial policies as identified by *Juhász, Lane, Oehlsen and Pérez* (2023) through a machine learning applied to *Global Trade Alert* data (2010-2022). Included countries: Belgium, Bulgaria, Cyprus, Czechia, Germany, Greece, Spain, France, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom.

Figure E.20: Regional productivity rises after an increase in industrial policy exposure

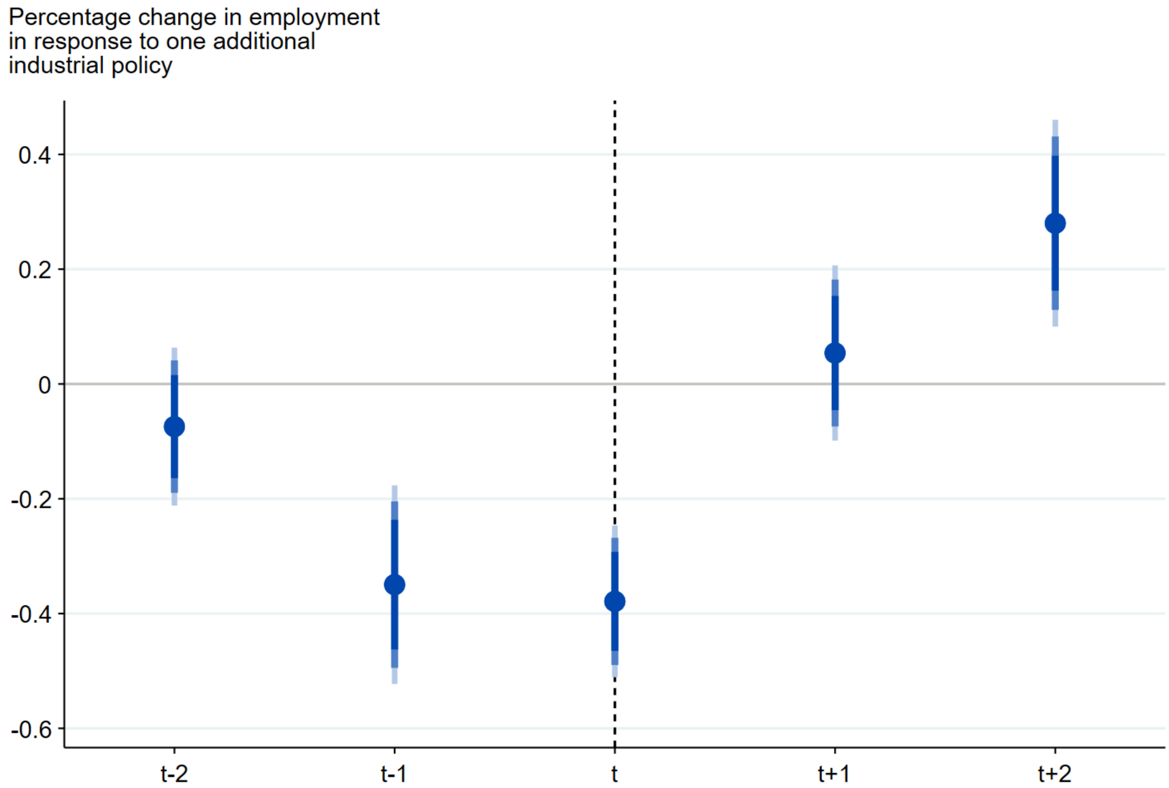
Coefficients from regressions of labour productivity on industrial policy exposure, UK and European regions, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, Eurostat and ONS data



Clustered standard errors at the region level. Labour productivity defined as Gross Value Added (GVA) divided by amount of hours worked. Labour productivity computed using data from *EUROSTAT and ONS* (2010-2022). Industrial policies as identified by *Juhász, Lane, Oehlsen and Pérez* (2023) through a machine learning algorithm applied to *Global Trade Alert* data (2010-2022). Included countries: Belgium, Bulgaria, Cyprus, Czechia, Germany, Greece, Spain,France, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom.

Figure E.21: Regional employment rises after an increase in industrial policy exposure

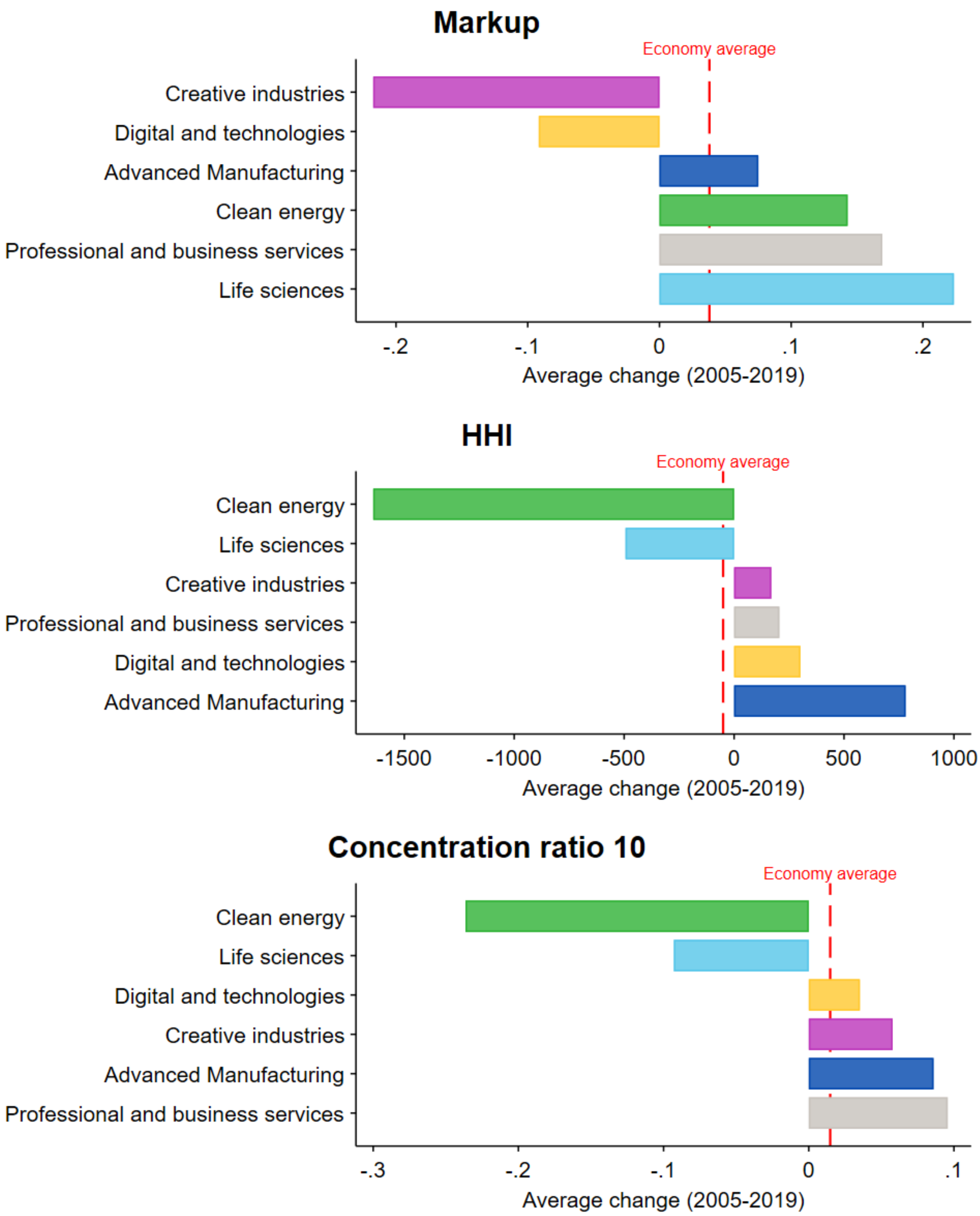
Coefficients from regressions of employment on industrial policy exposure, UK and European regions, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, Eurostat and ONS data



Clustered standard errors at the region level. Employment reflects hours worked data from *EUROSTAT and ONS* (2010-2022). Industrial policies as identified by *Juhász, Lane, Oehlsen and Pérez* (2023) through a machine learning applied to *Global Trade Alert* data (2010-2022). Included countries: Belgium, Bulgaria, Cyprus, Czechia, Germany, Greece, Spain, France, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom.

Figure E.22: Most key growth sectors experienced stronger-than-average growth in markups and concentration from 2005

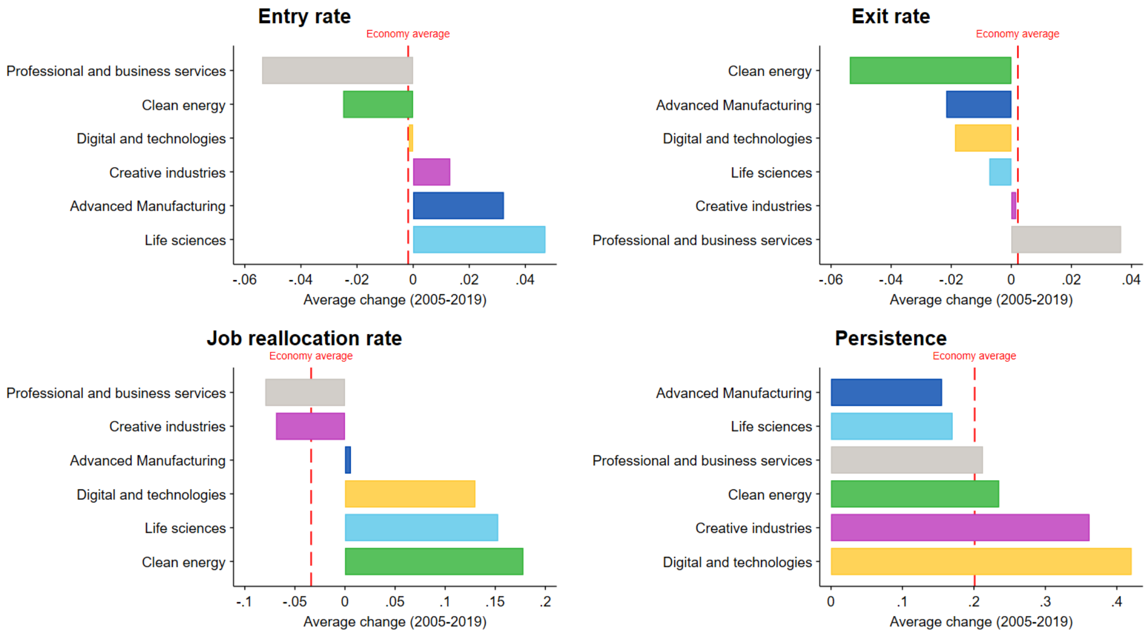
Market power and concentration measures for the growth-driving sectors, UK, average changes 2005-2019, from ONS business microdata



Long differences in static competition metrics in selected sectors. Sectoral averages obtained as turnover weighted averages of all industries included in the sector definition for which we have data. Sources: the *Annual Respondents Database* (1997-2020), the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

Figure E.23: Business dynamism has worsened according to at least one of the measures in all growth-driving sectors

Business dynamism measures for the growth-driving sectors, UK, average changes 2005-2019, from ONS business microdata



Long differences in business dynamism metrics in selected sectors. Sectoral averages obtained as turnover weighted averages of all industries included in the sector definition for which we have data. Data from the *Annual Respondents Database* (1997-2020), the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

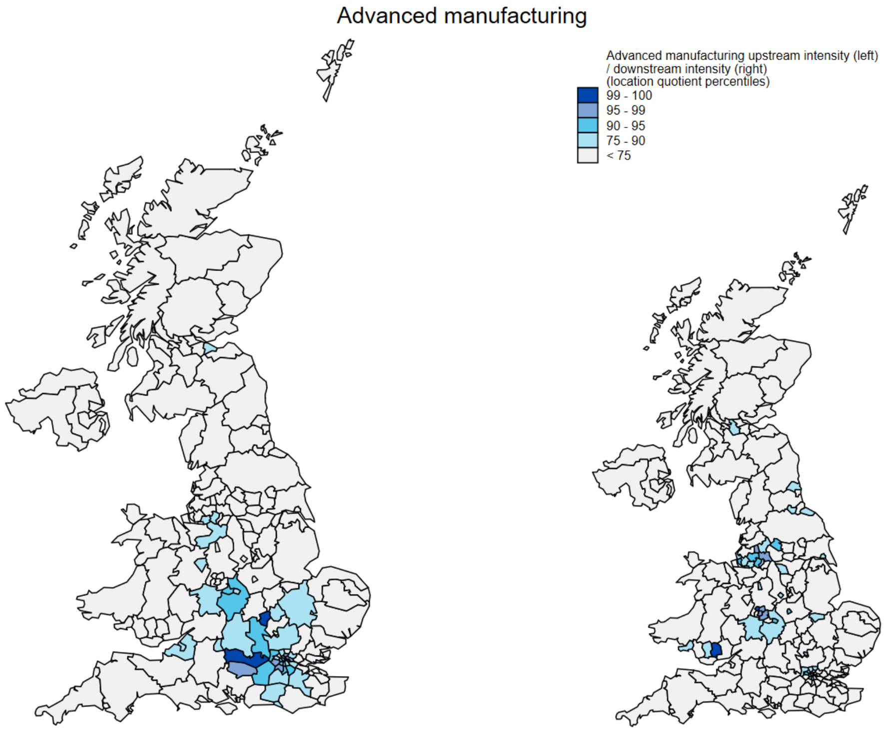
Figure E.24: R&D and productivity (but not investment) have increased more in the key growth sectors than the rest of the economy

Productivity, innovation and investment measures for the growth-driving sectors, UK, average changes 2005-2019 (2005-2017 for R&D), from ONS business microdata

Long differences in outcome variables in selected sectors. Sectoral averages obtained as turnover weighted averages of all industries included in the sector definition for which we have data. Data from the *Annual Respondents Database* (1997-2020), the *Annual Business Survey* (2021), the *Business Expenditure on Research and Development Database* (1995-2021), the *Business Structure Database* (1997-2022), the *Longitudinal Business Database* (1997-2021) and the *ONS Industry Level Deflators* (1997-2023).

Figure E.25: Upstream and downstream industries of advanced manufacturing are not very concentrated

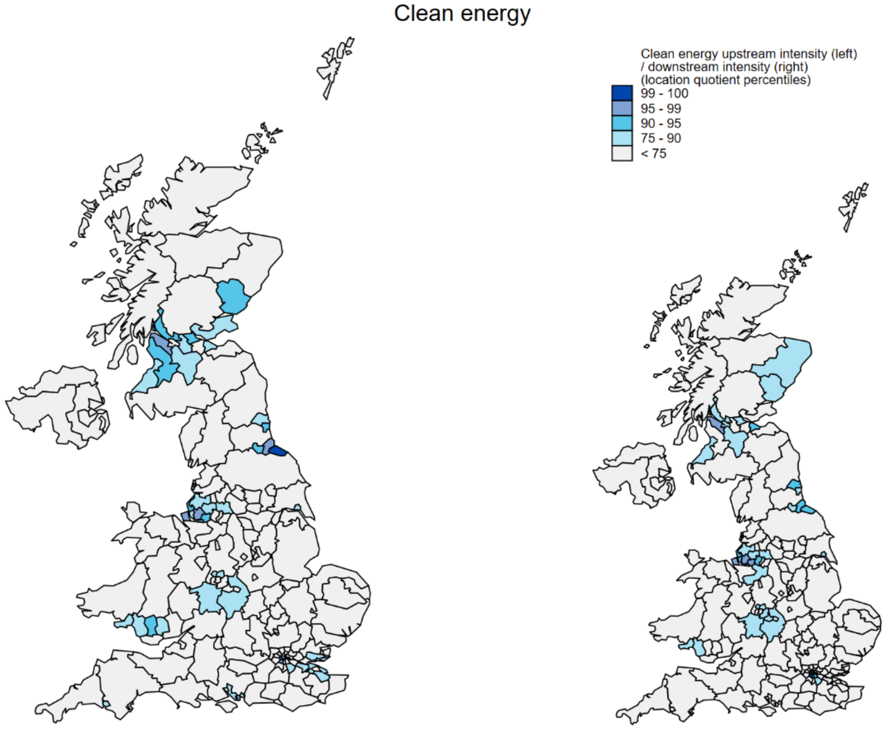
Establishment location quotients for industries upstream and downstream of advanced manufacturing, UK regions, 2024, from NOMIS data



Location quotients showing the ITL3 regions with the highest concentration of firms in sectors immediately upstream (left) and downstream (right) of the advanced manufacturing industry. The advanced manufacturing industry includes SIC codes: 20, 21, 254, 26, 27, 28, 29, 302, 303, 304, 309, 325. Upstream sectors are defined as those receiving the five highest total monthly payment flows from advanced manufacturing industry firms in the year 2024. This includes SIC codes: 651, 289, 829, 451, 620. Downstream sectors are defined as those giving the five highest total monthly payment flows to advanced manufacturing industry firms in the year 2024. These include SIC codes: 469, 829, 471, 451, 649. Sources: *NOMIS UK Business Counts* (2024); *ONS Industry-to-industry payment flows* (2024).

Figure E.26: Upstream and downstream industries of clean energy are quite dispersed

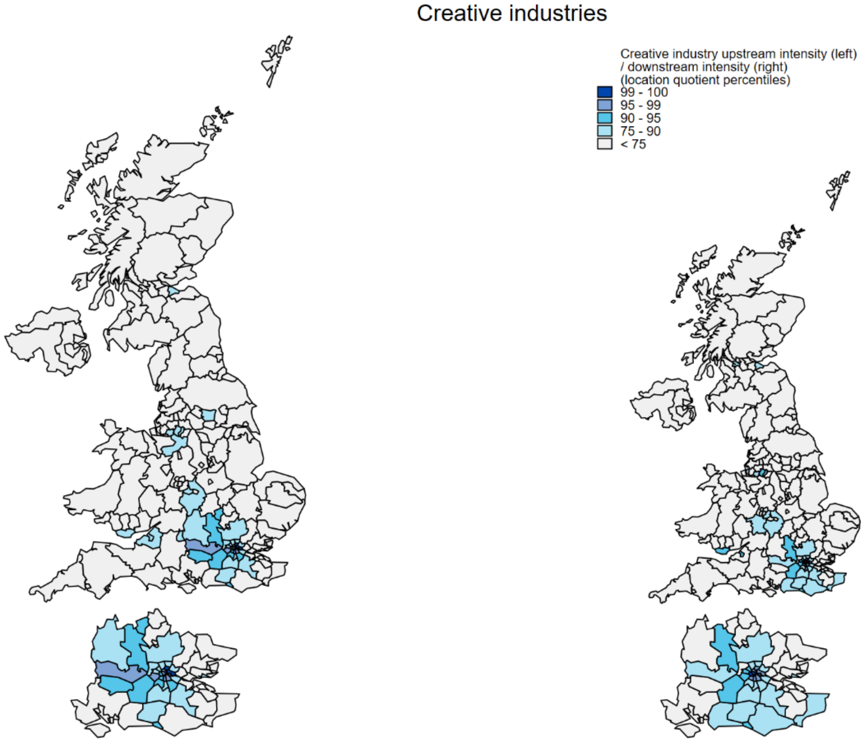
Establishment location quotients for industries upstream and downstream of clean energy, UK regions, 2024, from NOMIS data



Location quotients showing the ITL3 regions with the highest concentration of firms in sectors immediately upstream (left) and downstream (right) of the clean energy industry. The clean energy industry includes SIC codes: 271, 272, 2811, 35, 7112, 74901, and 721. Upstream sectors are defined as those receiving the five highest total monthly payment flows from clean energy industry firms in the year 2024. This includes SIC codes: 439, 351, 829, 749, 960. Downstream sectors are defined as those giving the five highest total monthly payment flows to clean energy industry firms in the year 2024. These include SIC codes: 960, 351, 749, 829, 701. Sources: *NOMIS UK Business Counts* (2024); *ONS Industry-to-industry payment flows* (2024).

Figure E.27: Upstream and downstream industries of creative industries are relatively concentrated in South East England and London

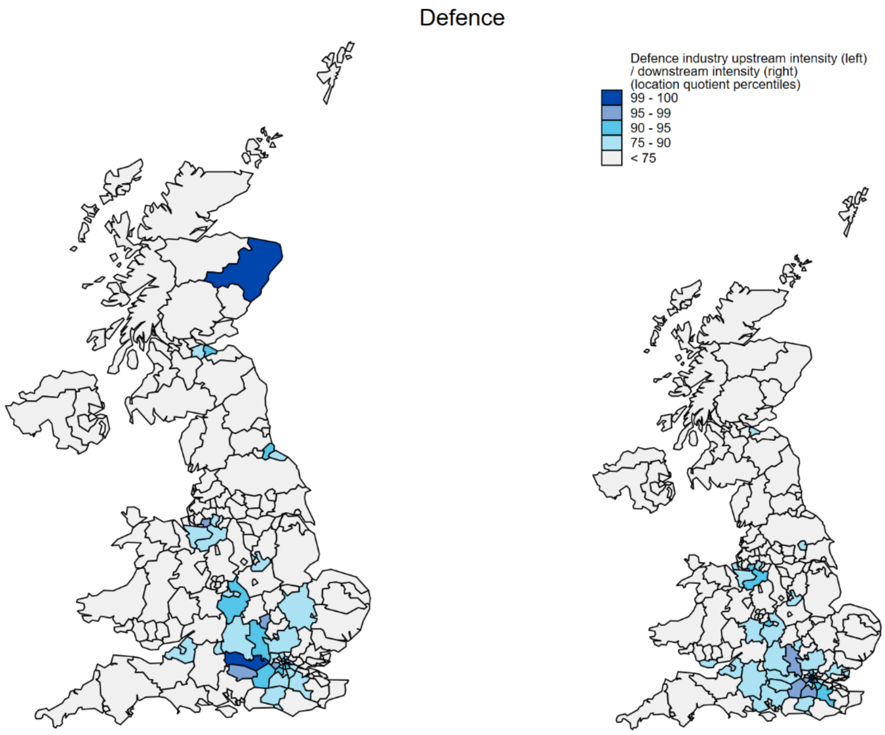
Establishment location quotients for industries upstream and downstream of creative industries, UK regions, 2024, from NOMIS data



Location quotients showing the ITL3 regions with the highest concentration of firms in sectors immediately upstream (above) and downstream (below) of the creative industries. The creative industries include SIC codes: 58, 59, 60, 62, 711, 731, 741, 472, 90 and 91. Upstream sectors are defined as those receiving the five highest total monthly payment flows from creative industries firms in the year 2024. This includes SIC codes: 620, 591, 829, 649, 731. Downstream sectors are defined as those giving the five highest total monthly payment flows to creative industries firms in the year 2024. These include SIC codes: 900, 591, 829, 649 and 522. Sources: *NOMIS UK Business Counts* (2024); *ONS Industry-to-industry payment flows* (2024).

Figure E.28: Upstream and downstream industries of defence are not very concentrated

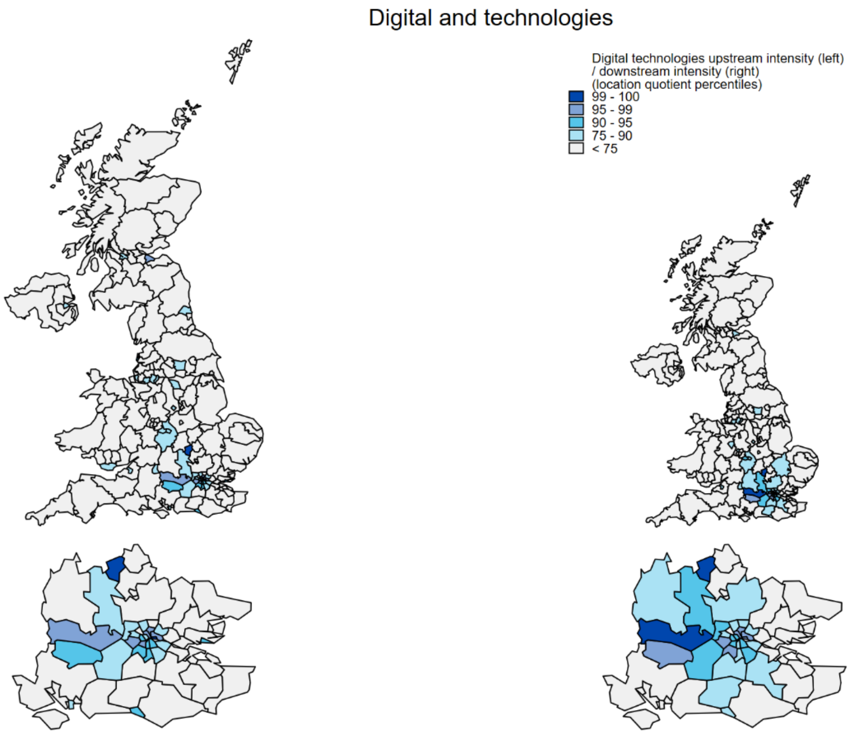
Establishment location quotients for industries upstream and downstream of defence, UK regions, 2024, from NOMIS data



Location quotients showing the ITL3 regions with the highest concentration of firms in sectors immediately upstream (left) and downstream (right) of the defence industry. The defence industry includes SIC codes: 254, 304 and 8422. Upstream sectors are defined as those receiving the five highest total monthly payment flows from defence industry firms in the year 2024. These include SIC codes: 620, 303, 829, 711, 651. Downstream sectors are defined as those giving the five highest total monthly payment flows to defence industry firms in the year 2024. These include SIC codes: 862, 303, 829, 783, 702. Sources: *NOMIS UK Business Counts* (2024); *ONS Industry-to-industry payment flows* (2024).

Figure E.29: Upstream and downstream industries of digital and technology are fairly concentrated in South East England and London

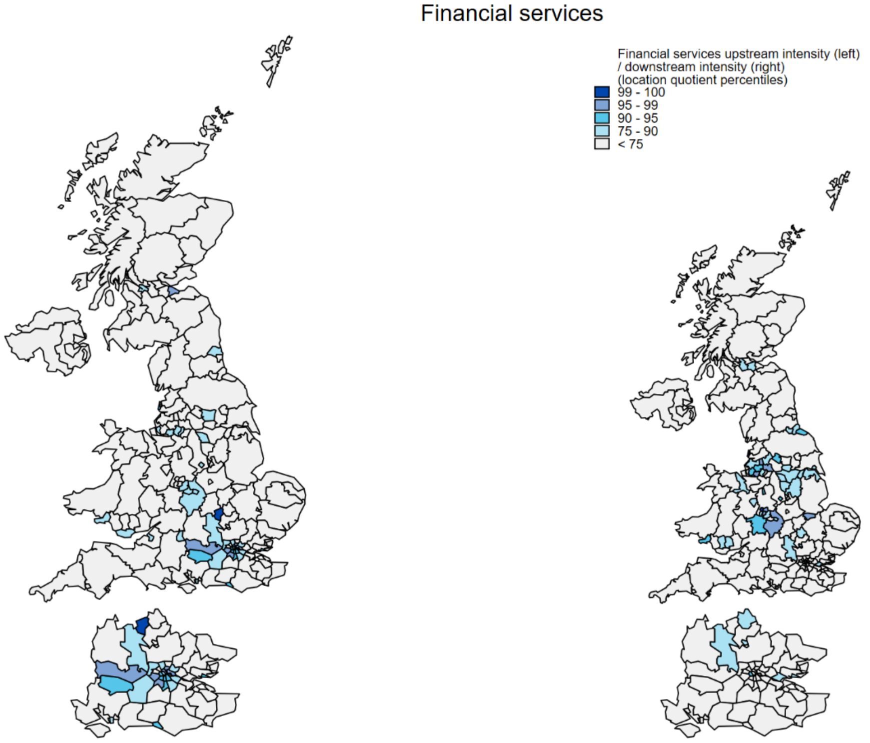
Establishment location quotients for industries upstream and downstream of digital and technology, UK regions, 2024, from NOMIS data



Location quotients showing the ITL3 regions with the highest concentration of firms in sectors immediately upstream (left) and downstream (right) of the digital and technologies industry. The digital and technologies industry includes SIC codes: 58, 59, 60, 61, 62, 63, 8299. Upstream sectors are defined as those receiving the five highest total monthly payment flows from digital and technologies industry firms in the year 2024. These include SIC codes: 620, 829, 561, 619 and 649. Downstream sectors are defined as those giving the five highest total monthly payment flows to digital and technologies firms in the year 2024. These include SIC codes: 619, 620, 829, 649, 522. Sources: *NOMIS UK Business Counts* (2024); *ONS Industry-to-industry payment flows* (2024).

Figure E.30: Upstream and downstream industries of financial services are concentrated in urban centres around the country, particularly Greater London

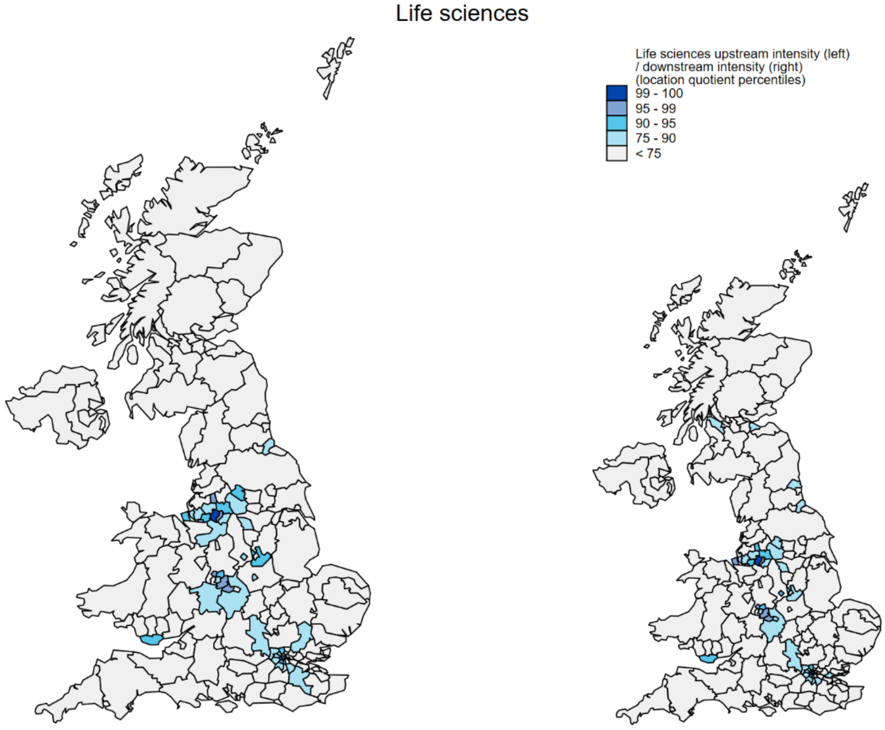
Establishment location quotients for industries upstream and downstream of financial services, UK regions, 2024, from NOMIS data



Location quotients showing the ITL3 regions with the highest concentration of firms in sectors immediately upstream (above) and downstream (below) of the financial services industry. The financial services industry includes SIC codes: 64, 65 and 66. Upstream sectors are defined as those receiving the five highest total monthly payment flows from financial services industry firms in the year 2024. These include SIC codes: 649, 451, 829, 561 and 620. Downstream sectors are defined as those giving the five highest total monthly payment flows to financial services industry firms in the year 2024. These include SIC codes: 649, 451, 829, 651 and 452.
Sources: *NOMIS UK Business Counts* (2024); *ONS Industry-to-industry payment flows* (2024).

Figure E.31: Industries upstream and downstream of life sciences are fairly concentrated in London, the West Midlands and the North West

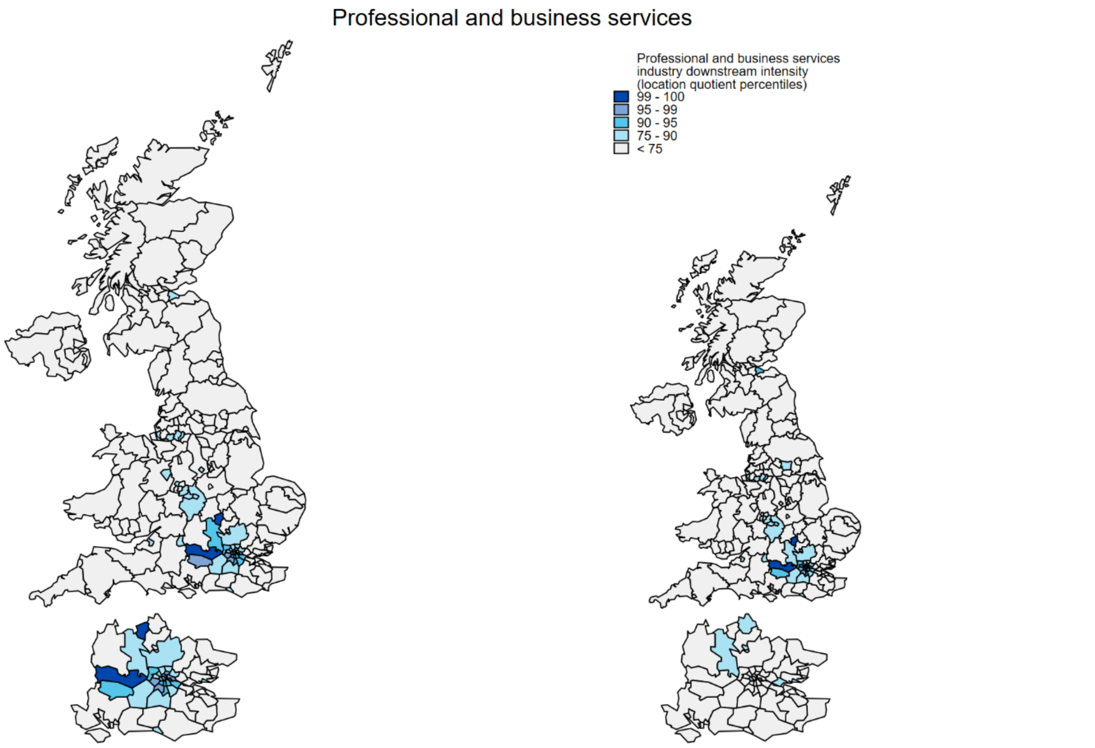
Establishment location quotients for industries upstream and downstream of life sciences, UK regions, 2024, from NOMIS data



Location quotients showing the ITL3 regions with the highest concentration of firms in sectors immediately upstream (left) and downstream (right) of the life sciences industry. The life sciences industry includes SIC codes: 21, 325, 721, 86 and 266. Upstream sectors are defined as those receiving the five highest total monthly payment flows from life sciences industry firms in the year 2024. These include SIC codes: 862, 464, 869, 841 and 829. Downstream sectors are defined as those giving the five highest total monthly payment flows to life sciences industry firms in the year 2024. These include SIC codes: 649, 829, 862, 869 and 522. Sources: *NOMIS UK Business Counts* (2024); *ONS Industry-to-industry payment flows* (2024).

Figure E.32: Industries upstream and downstream of professional and business services are fairly concentrated in London and South East England

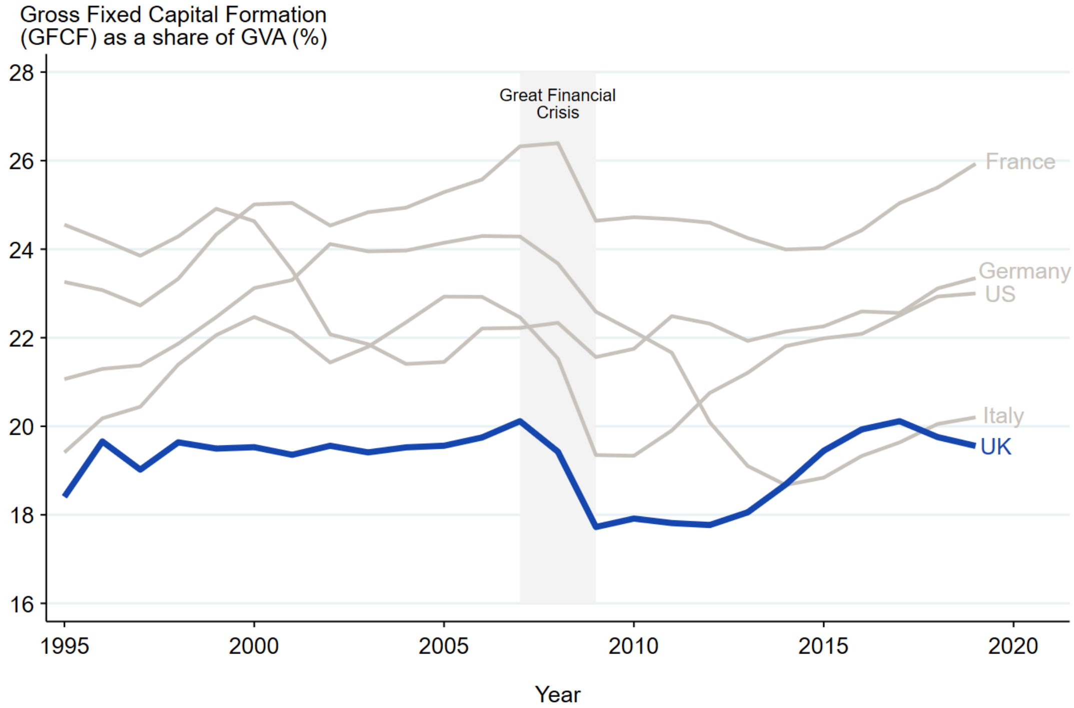
Establishment location quotients for industries upstream and downstream of professional and business services, UK regions, 2024, from NOMIS data



Location quotients showing the ITL3 regions with the highest concentration of firms in sectors immediately upstream (above) and downstream (below) of the professional and business services industry. The professional and business services industry includes SIC codes: 69, 70, 71, 73, 78, 82, 411, 74, 77 and 81. Upstream sectors are defined as those receiving the five highest total monthly payment flows from professional and business services industry firms in the year 2024. These include SIC codes: 829, 841, 649, 620, 471. Downstream sectors are defined as those giving the five highest total monthly payment flows to professional and business services industry firms in the year 2024. These include SIC codes: 841, 829, 649, 620 and 471. Sources: *NOMIS UK Business Counts* (2024); *ONS Industry-to-industry payment flows* (2024).

Figure E.33: The UK has invested less than comparable countries for many years

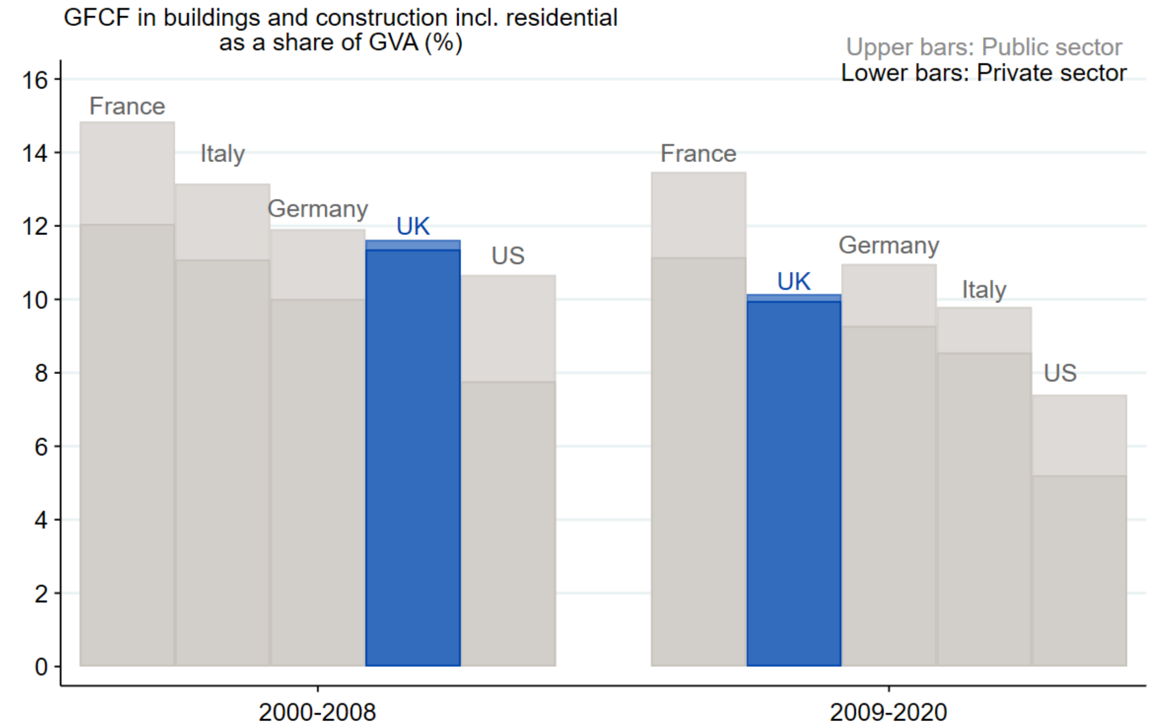
Gross Fixed Capital Formation as a share of GVA, UK and peers, 1995-2019, from the EUKLEMS database



Gross Fixed Capital Formation (GFCF) as a share of Gross Value Added (GVA) (%) (1995-2019). Calculated using real GFCF and GVA volumes with 2015 reference prices. Included countries: France, Germany, Italy, United Kingdom and United States. Source: *EUKLEMS INTANProd database* (1995-2019).

Figure E.34: UK investment in buildings and construction, including residential, is generally lower than in peer countries, and predominantly provided by the private sector

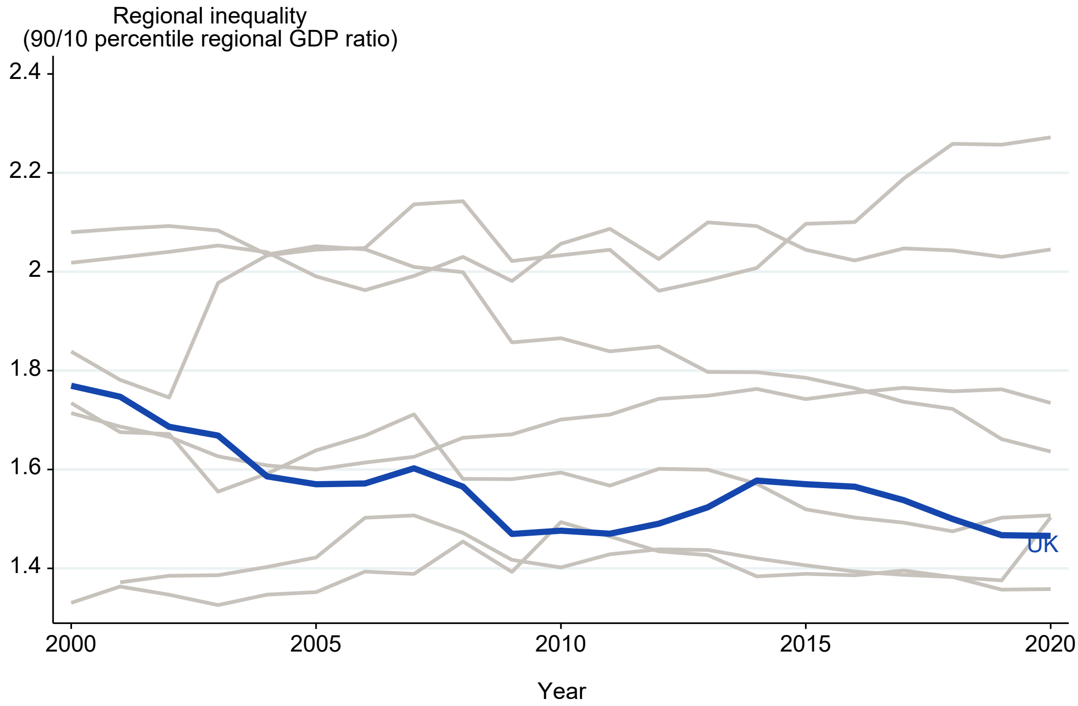
Investment in buildings and construction, including residential, as a share of GVA, public and private sector, UK and OECD peers, 2000-2020, from the EUKLEMS and INTANProd database



Gross fixed capital formation (GFCF) in construction as a share of gross value added (GVA) (%), averaged over the sub-periods 2000-2008 and 2009-2020. GFCF and GVA are volume measures (prices of 2020). Public investment is proxied by that in Public administration, defence, education, human health and social work activities (O-Q). Private sector includes residential investment in real estate. Public is investment of sections O-Q. Source: EUKLEMS & INTANProd database.

Figure E.35: The UK has a low and falling 90-10 percentile ratio of regional inequality at ITL2 level

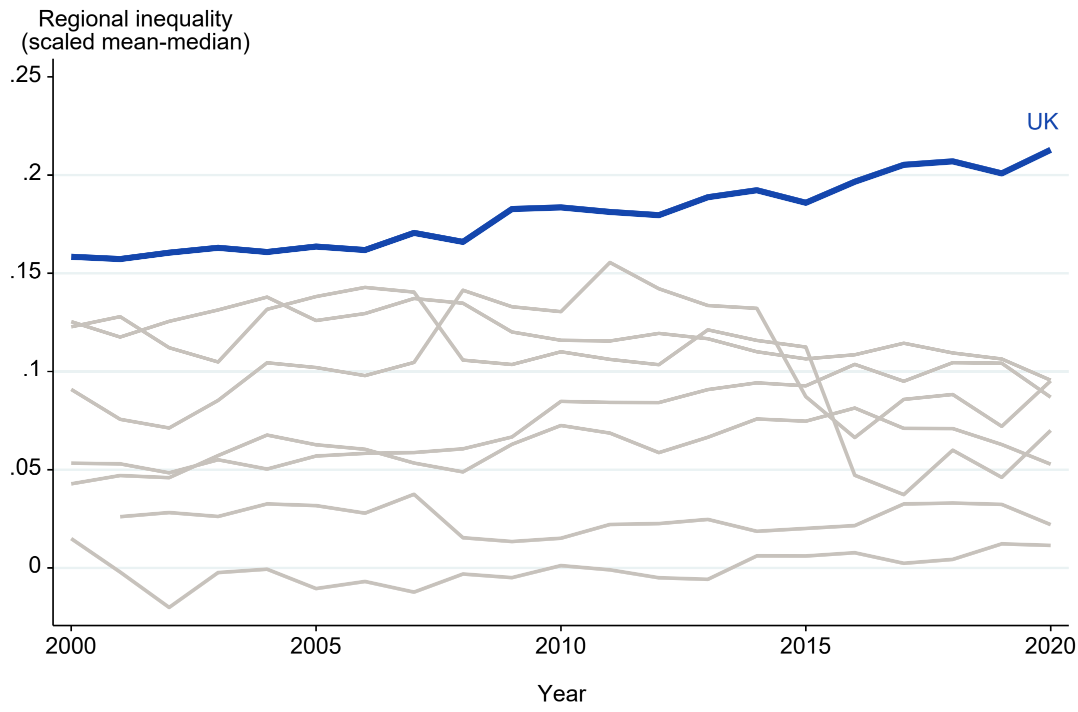
Regional inequality as measured by the ratio of the 90th to 10th percentiles of GDP per capita for each country, 2000-2020, OECD



We use GDP per capita data (USD PPP at constant 2015 prices) at the ITL2 level from *OECD* (2000-2020). We take the 90th and 10th percentile for each country in each year. We then divide the 90th percentile by the 10th. Included countries: France, Germany, Italy, Korea, Norway, Spain, UK and USA.

Figure E.36: The UK has a high and rising mean-median ratio of regional inequality at ITL3 level

Regional inequality as measured by the mean to median ratio of GDP per capita for each country, 2000-2020, OECD

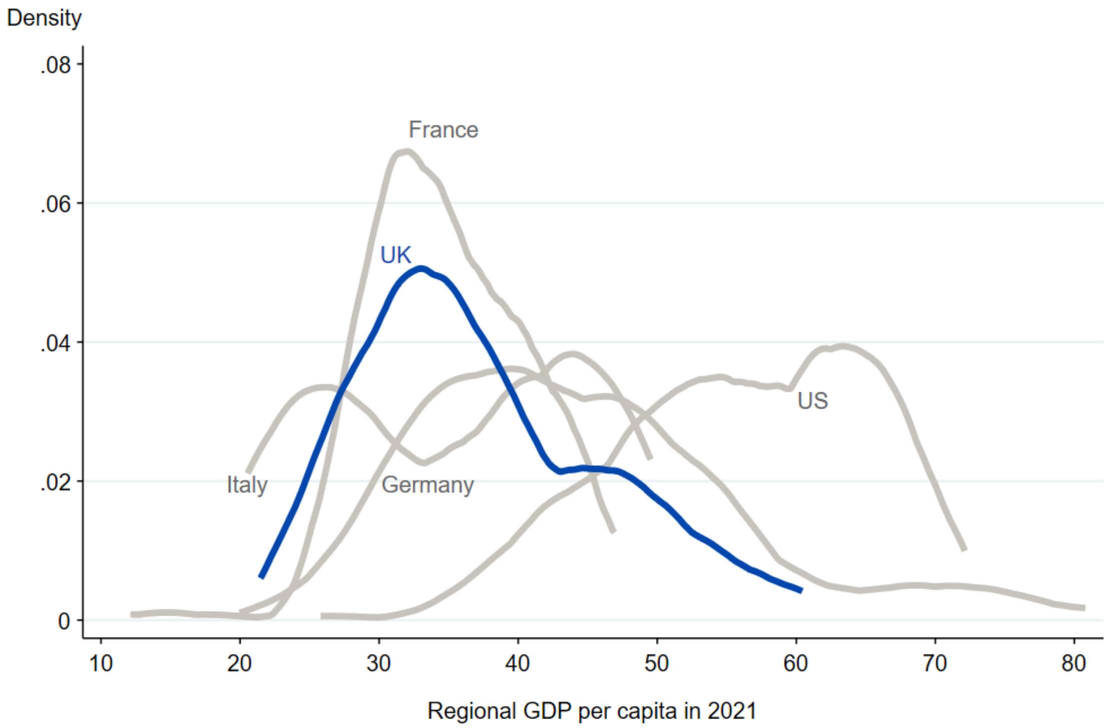


We use GDP per capita data (USD PPP at constant 2015 prices) at the ITL3 level from *OECD* (2000-2020). We look at the difference between the mean and the median. We then scale this difference by the mean. Included countries: France, Germany, Italy, Korea, Norway, Spain, UK and USA.

Germany

Figure E.37: Regional GDP inequality in the UK is predominantly driven by a long upper tail

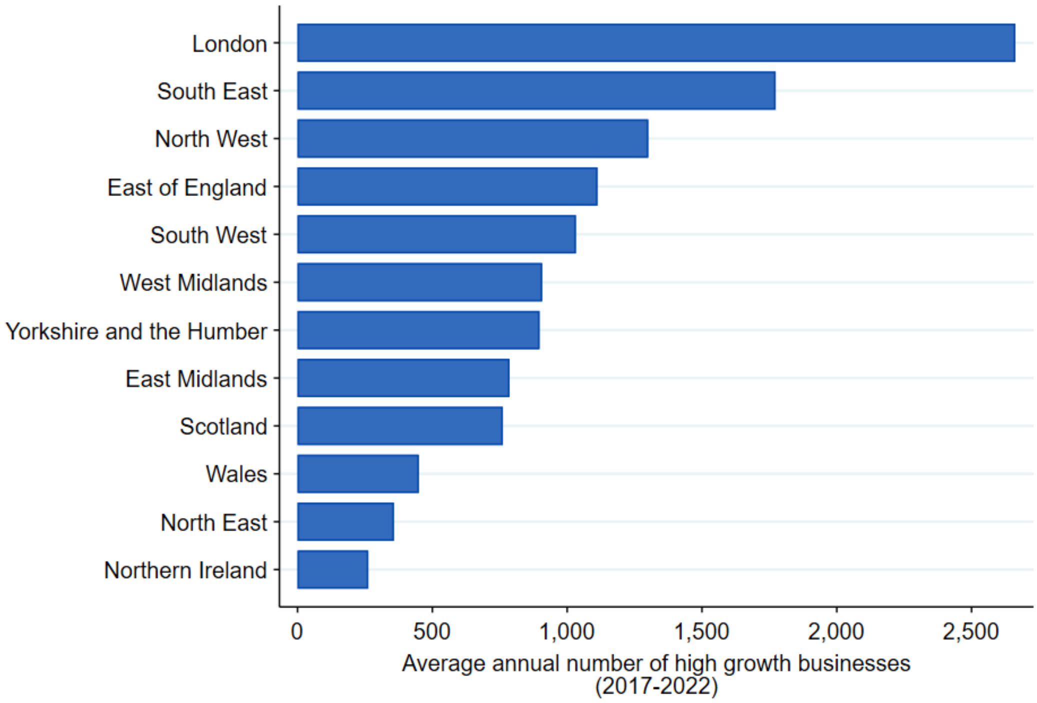
Density plot of GDP per capita weighted by population, ITL3 regions, 2021, OECD



In thousand *USD*, 2015 prices, Purchasing Power Parities. Densities weighted by regional population share. Computed using data for ITL3 regions. *Source: OECD Regional database* (2021).

Figure E.38: UK high-growth businesses are concentrated in London and the South East

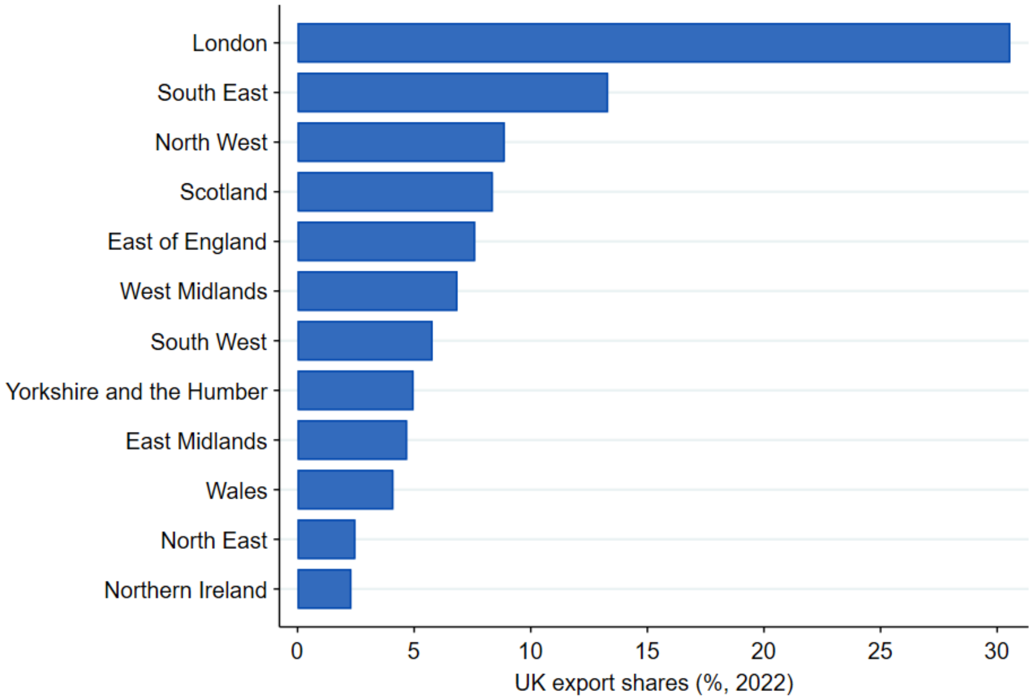
Unadjusted High-growth businesses per 100,000 people, UK regions and nations, 2017-2022, from the ONS local indicators dataset



High growth businesses are defined as those with an average growth in employment of greater than 20% per year over a three-year period.
Sources: *ONS Local Indicators dataset* (2017-2022).

__Figure E.39: UK exports are concentrated in London__

Unadjusted share of UK exports, UK regions and Nations, 2022, from the ONS local indicators dataset



Derived from estimates of the total value of UK exports including trade in both goods and services. Source: *ONS Local Indicators dataset* (2022).

F. Additional tables

Table 1: Industrial policies tend to target more productive industries, where they can have small positive effects

Coefficients from regressions of labour productivity on industrial policy spending, 2019-2022, from QuIS and the OECD national accounts database. Robust standard errors

Labour productivity	(1)	(2)	(3)	(4)
Lagged industrial policy spending	2.55***	2.54***	2.27***	0.16
	(0.49)	(0.49)	(0.25)	(0.25)
Observations	598	598	598	598
R-squared	0.03	0.03	0.60	0.93
Year FEs		X	X	X
Country FEs			X	X
SIC FEs				X

Note: labour productivity defined as Gross Value Added (GVA) divided by the amount of hours worked. Included countries: Canada, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Data from* OECD *(2019-2022) and* Quantifying Industrial Strategies *(2019-2022). Fixed effects included are indicated by an X. Robust standard errors are reported in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 2: Industrial policies tend to target more productive industries, where they can have small positive effects

Coefficients from regressions of labour productivity on industrial policy spending, 2019-2022, from the OECD national accounts database. Clustered standard errors

Labour productivity	(1)	(2)	(3)	(4)
Lagged industrial policy spending	2.55***	2.54***	2.27***	0.16
	(0.79)	(0.80)	(0.38)	(0.37)
Observations	598	598	598	598
R-squared	0.03	0.03	0.60	0.93
Year FEs		X	X	X
Country FEs			X	X
SIC FEs				X

Note: labour productivity defined as Gross Value Added (GVA) divided by the amount of hours worked. Included countries: Canada, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Data from OECD (2019-2022) and Quantifying Industrial Strategies (2019-2022). Fixed effects included are indicated by X. Standard errors are clustered at the industry by country level and are reported in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 3: Industrial policy spending is followed by small productivity gains, while there is no clear effect of industrial policy on employment, investment or R&D

Coefficients from regressions of (1) labour productivity (2) hours worked, (3) investment and (4) R&D on industrial policy spending, 2019-2022, from the OECD national accounts database. Robus standard errors

Industrial policy spending	(1) t-2	(2) t-1	(3) t	(4) t+1	(5) t+2
Productivity	-0.31***	-0.35**	-0.26	0.16	0.23
	(0.10)	(0.17)	(0.21)	(0.25)	(0.32)
Observations	398	598	798	598	398
R-squared	0.94	0.94	0.93	0.93	0.93
Hours worked	0.16	0.07	-0.02	-0.31	-0.40
	(0.12)	(0.14)	(0.14)	(0.25)	(0.30)
Observations	398	598	798	598	398
R-squared	0.95	0.95	0.95	0.95	0.95
Investment	-0.29	-0.17	-0.29	-0.48	-0.47
	(0.95)	(0.66)	(0.55)	(0.64)	(0.72)
Observations	272	401	511	382	253
R-squared	0.85	0.86	0.85	0.85	0.85
R&D	0.34	0.58	-0.61	-0.69	-1.67
	(1.51)	(1.29)	(1.01)	(1.26)	(1.97)
Observations	232	333	371	255	139
R-squared	0.88	0.89	0.89	0.89	0.90

Note: labour productivity defined as Gross Value Added (GVA) divided by the amount of hours worked. Included countries: Canada, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Data from OECD (2019-2022) and Quantifying Industrial Strategies (2019-2022). Time, country and industry fixed effects included. Robust standard errors are clustered at the industry by country level and are reported in parentheses.
****** p<0.01, ** p<0.05, * p<0.1***

Table 4: Industrial policy spending is followed by small productivity gains, while there is no clear effect of industrial policy on employment, investment or R&D

Coefficients from regressions of (1) labour productivity (2) hours worked, (3) investment and (4) R&D on industrial policy spending, 2019-2022, from the OECD national accounts database. Clustered standard errors

Industrial policy spending	(1) t-2	(2) t-1	(3) t	(4) t+1	(5) t+2
Productivity	-0.31**	-0.35*	-0.26	0.16	0.23
	(0.12)	(0.19)	(0.24)	(0.37)	(0.40)
Observations	398	598	798	598	398
R-squared	0.94	0.94	0.93	0.93	0.93
Hours worked	0.16	0.07	-0.02	-0.31	-0.40
	(0.15)	(0.19)	(0.21)	(0.41)	(0.40)
Observations	398	598	798	598	398
R-squared	0.95	0.95	0.95	0.95	0.95
Investment	-0.29	-0.17	-0.29	-0.48	-0.47
	(1.30)	(1.06)	(0.98)	(0.97)	(0.92)
Observations	272	401	511	382	253
R-squared	0.85	0.86	0.85	0.85	0.85
R&D	0.34	0.58	-0.61	-0.69	-1.67
	(1.89)	(1.63)	(1.35)	(1.46)	(2.28)
Observations	232	333	371	255	139
R-squared	0.88	0.89	0.89	0.89	0.90

Note: labour productivity defined as Gross Value Added (GVA) divided by the amount of hours worked. Included countries: Canada, France, Germany, Ireland, Italy, Netherlands, Slovenia, Sweden, and the UK. Data from OECD (2019-2022) and Quantifying Industrial Strategies (2019-2022). Time, country and industry fixed effects included. Standard errors are clustered at the industry by country level and are reported in parentheses.
****** p<0.01, ** p<0.05, * p<0.1***

Table 5: There is no clear effect of industrial policy on markups

Coefficients from regressions of (1) markups on industrial policy counts, 2010-2022, from the OECD national accounts database. Robust standard errors

Markups	(1) t-2	(2) t-1	(3) t	(4) t+1	(5) t+2
Industrial policy counts	0.0011**	0.0011***	0.0012***	0.0012***	0.0010**
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Observations	1,659	1,848	2,037	1,848	1,659
R-squared	0.4589	0.4522	0.4427	0.4426	0.4382

Note: Markup data from CompNet database (2010-2021) and is estimated using the production function approach (Ordinary Least Square estimation of a translog production function, with materials as flexible input). Top and bottom 1% markups in each year have been excluded. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to Global Trade Alert data (2010-2021). Included countries: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Latvia, Lithuania, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the UK. Time, country and industry fixed effects included. Robust standard errors are reported in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 6: There is no clear effect of industrial policy on markups

Coefficients from regressions of (1) markups on industrial policy counts, 2010-2022, from the OECD national accounts database. Robust standard errors

Markups	(1) t-2	(2) t-1	(3) t	(4) t+1	(5) t+2
Industrial policy counts	0.0011	0.0011	0.0012	0.0012	0.0010
	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Observations	1,659	1,848	2,037	1,848	1,659
R-squared	0.4589	0.4522	0.4427	0.4426	0.4382

Note: Markup data from CompNet database (2010-2021) and is estimated using the production function approach (Ordinary Least Square estimation of a translog production function, with materials as flexible input). Top and bottom 1% markups in each year have been excluded. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to Global Trade Alert data (2010-2021). Included countries: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Latvia, Lithuania, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the UK. Time, country and industry fixed effects included. Standard errors are clustered at the industry by year level and are reported in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 7: Tax credits appear to be most effective at raising productivity

Coefficients from regressions of labour productivity on industrial policy count, by instrument type, 2019-2022, from the OECD national accounts database. Robust standard errors

Labour productivity	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged tax reliefs	0.0918						
	(0.0656)						
Lagged state loans		0.0150***					
		(0.0037)					
Lagged loan guarantees			0.0138*				
			(0.0071)				
Lagged financial and in-kind grants				0.0050			
				(0.0032)			
Lagged trade finance and measures					0.0024***		
					(0.0006)		
Lagged other IS policies						-0.0096	
						(0.0096)	
Lagged capital injections and equity stakes							-0.0132
							(0.0111)
Observations	7,659	7,659	7,659	7,659	7,659	7,659	7,659
R-squared	0.9410	0.9411	0.9410	0.9410	0.9410	0.9410	0.9410

Note: labour productivity defined as Gross Value Added divided by the amount of hours worked. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to Global Trade Alert dat. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Data from the Global Trade Alert data (2010-2022) and OECD (2010-2022). Time, country and industry fixed effects included. Robust standard errors are reported in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 8: Tax credits appear to be most effective at raising productivity

Coefficients from regressions of labour productivity on industrial policy count, by instrument type, 2019-2022, from the OECD national accounts database. *Clustered standard errors*

Labour productivity	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged tax reliefs	0.0918						
	(0.0655)						
Lagged state loans		0.0150*					
		(0.0077)					
Lagged loan guarantees			0.0138				
			(0.0097)				
Lagged financial and in-kind grants				0.0050			
				(0.0043)			
Lagged trade finance and measures					0.0024**		
					(0.0012)		
Lagged other IS policies						-0.0096	
						(0.0129)	
Lagged capital injections and equity stakes							-0.0132
							(0.0183)
Observations	7,659	7,659	7,659	7,659	7,659	7,659	7,659
R-squared	0.9410	0.9411	0.9410	0.9410	0.9410	0.9410	0.9410

Note: labour productivity defined as Gross Value Added divided by the amount of hours worked. Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to Global Trade Alert data. Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Data from the Global Trade Alert data (2010-2022) and OECD (2010-2022). Time, country and industry fixed effects included. Standard errors are clustered at the industry by country level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Industrial policies are positively related to productivity in production

Coefficients from regressions of labour productivity on industrial policy spending, for production, 2019-2022, from the OECD national accounts database. Robust standard errors

Labour productivity	(1)	(2)	(3)	(4)
Lagged industrial policy counts	0.0220***	0.0209***	0.0041***	0.0017**
	(0.0033)	(0.0031)	(0.0014)	(0.0009)
Observations	2,297	2,297	2,297	2,297
R-squared	0.0128	0.0175	0.7921	0.9463
Year FEs		X	X	X
Country FEs			X	X
SIC FEs				X

Note: This regression only includes service sectors. We define labour productivity as Gross Value Added (GVA) divided by hours worked. This data comes from OECD (2010-2023). Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to Global Trade Alert data (2010-2022). Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Fixed effects included are indicated by an X. Robust standard errors are reported in parentheses.
****** p<0.01, ** p<0.05, * p<0.1***

Table 10: Industrial policies are positively related to productivity in production

Coefficients from regressions of labour productivity on industrial policy spending, for production, 2019-2022, from the OECD national accounts database. Clustered standard errors

Labour productivity	(1)	(2)	(3)	(4)
Lagged industrial policy counts	0.0220***	0.0209***	0.0041***	0.0017**
	(0.0072)	(0.0067)	(0.0028)	(0.0018)
Observations	2,297	2,297	2,297	2,297
R-squared	0.0128	0.0175	0.7921	0.9463
Year FEs		X	X	X
Country FEs			X	X
SIC FEs				X

Note: This regression excludes non-service sectors. We define labour productivity as Gross Value Added (GVA) divided by hours worked. This data comes from OECD (2010-2023). Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to Global Trade Alert data (2010-2022). Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Fixed effects included are indicated by X. Standard errors are clustered at the industry by country level and are reported in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 11: Industrial policies are not positively related to productivity in services

Coefficients from regressions of labour productivity on industrial policy spending, for services, 2019-2022, from the OECD national accounts database. Robust standard errors

Labour productivity	(1)	(2)	(3)	(4)
Lagged industrial policy counts	0.1216***	0.1061***	0.0303***	-0.0045*
	(0.0201)	(0.0187)	(0.0059)	(0.0024)
Observations	5,362	5,362	5,362	5,362
R-squared	0.0073	0.0125	0.7615	0.9458
Year FEs		X	X	X
Country FEs			X	X
SIC FEs				X

Note: This regression only includes service sectors. We define labour productivity as Gross Value Added (GVA) divided by hours worked. This data comes from OECD (2010-2023). Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to Global Trade Alert data (2010-2022). Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Fixed effects included are indicated by an X. Robust standard errors are reported in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 12: Industrial policies are not positively related to productivity in services

Coefficients from regressions of labour productivity on industrial policy spending, for services, 2019-2022, from the OECD national accounts database. Clustered standard errors

Labour productivity	(1)	(2)	(3)	(4)
Lagged industrial policy counts	0.1216***	0.1061***	0.0303**	-0.0045
	(0.0309)	(0.0291)	(0.0124)	(0.0043)
Observations	2,297	2,297	2,297	2,297
R-squared	0.0073	0.0125	0.7615	0.9458
Year FEs		X	X	X
Country FEs			X	X
SIC FEs				X

Note: This regression only includes service sectors. We define labour productivity as Gross Value Added (GVA) divided by hours worked. This data comes from OECD (2010-2023). Industrial policies as identified by Juhász, Lane, Oehlsen and Pérez (2023) through a machine learning algorithm applied to Global Trade Alert data (2010-2022). Included countries: Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, UK, and US. Fixed effects included are indicated by X. Standard errors are clustered at the industry by country level and are reported in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 13: Regional productivity and regional employment rise after an increase in industrial policy exposure

Coefficients from regressions of a) labour productivity and b) hours worked on industrial policy exposure, UK and European regions, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, Eurostat and ONS data. Robust standard errors

	(1)	(2)	(3)	(4)	(5)
Industrial Policy Exposure	t-2	t-1	t	t+1	t+2
Labour Productivity	-0.006***	-0.006***	-0.007***	-0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,691	2,956	3,221	2,956	2,691
R-squared	0.990	0.989	0.988	0.989	0.990
Hours Worked	-0.001	-0.003***	-0.004***	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,691	2,956	3,221	2,956	2,691
R-squared	0.999	0.998	0.998	0.998	0.999

Note: Data from the ONS (2010-2022), EUROSTAT Structural Business Survey (2010-2022) and Juhász, Lane, Oehlsen and Pérez' machine learning analysis of the Global Trade Alert database (2010-2022). Labour productivity is defined as Gross Value Added (GVA) divided by hours worked. Included countries: Belgium, Bulgaria, Cyprus, Czechia, Germany, Greece, Spain, France, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and the U K. Fixed effects at the reporting unit and year level. Robust standard errors are reported below the regression coefficients in parentheses.

****** p<0.01, ** p<0.05, * p<0.1***

Table 14: Regional productivity and regional employment rise after an increase in industrial policy exposure

Coefficients from regressions of a) labour productivity and b) hours worked on industrial policy exposure, UK and European regions, 2010-2022, from Juhász, Lane, Oehlsen and Pérez (2023) and the Global Trade Alert database, Eurostat and ONS data. Clustered standard errors

Industrial Policy Exposure	(1) t-2	(2) t-1	(3) t	(4) t+1	(5) t+2
Labour Productivity	-0.006***	-0.006***	-0.007***	-0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,691	2,956	3,221	2,956	2,691
R-squared	0.990	0.989	0.988	0.989	0.990
Hours Worked	-0.001	-0.003***	-0.004***	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,691	2,956	3,221	2,956	2,691
R-squared	0.999	0.998	0.998	0.998	0.999

Note: Data from the ONS (2010-2022), EUROSTAT Structural Business Survey (2010-2022) and Juhász, Lane, Oehlsen and Pérez' machine learning analysis of the Global Trade Alert database (2010-2022). Labour productivity is defined as Gross Value Added (GVA) divided by hours worked. Included countries: Belgium, Bulgaria, Cyprus, Czechia, Germany, Greece, Spain, France, Hungary, Ireland, Italy, Lithuania, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and the UK. Fixed effects at the reporting unit and year level. Standard errors are reported below the regression coefficients in parentheses. They are clustered at the region level.
****** p<0.01, ** p<0.05, * p<0.1***