The State of UK Competition

CMA Microeconomics Unit

24 October 2024

Report no. 2

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1 Executive summary

Overview

1.1 Competitive, well-functioning markets matter to all of us. The pressure of competition, and the rewards of success, drive firms to keep prices low; to improve the quality of their products and services; to innovate; and to operate more efficiently. This benefits people, who get better deals; businesses, which reap the benefits of investment and innovation; and the wider economy, through higher productivity and living standards.

1.2 This is the CMA's third report on the State of UK Competition. First commissioned in 2020 by the then Chancellor and Business Secretary, the central aim of these reports is to provide the best available information and analysis on competition and market power across the UK economy. While the objective of the commission is to help inform public debate and policy, there are limits to how far assessments of competition at a cross-economy level can meaningfully guide economic policy choices. Accordingly, as the government looks to address long-standing challenges that hold back the UK's economic performance, the CMA intends to build on the findings in this report in a way that supports and informs this, including through the work of its Microeconomic Unit set out in paragraph [1.44], below.

1.3 The CMA's purpose is to help people, businesses and the UK economy by promoting competitive markets and tackling unfair behaviour. Through its work, therefore, the CMA influences competitive conditions. Merger control, for example, stops the growth in market power that might otherwise result from anti-competitive acquisitions. Competition enforcement stops firms avoiding competitive pressure by colluding, or by abusing their dominant positions.

1.4 Although this report is not a review of the CMA's performance, our findings provide a guide to the overall effectiveness of competition policy in the UK over time. With each successive report, we have sought to update previous indicators, and to refine and improve our analysis, to reflect the best available data, the most robust methodology, and the latest developments in the theory and measurement of competition and market power. Accordingly, this report represents the most comprehensive and rigorous assessment to date of the state of UK competition.

1.5 As we set out below, our central measure of market power (cost markups) indicates that the UK has seen a modest weakening of competition over the last 25 years. However, this change appears to be less pronounced in the UK than in many other advanced economies, including the US. There is also evidence that effective competition policy has kept the growth of market power in check: in particular, evidence from the US linking M&A activity to rising markups is not mirrored in the UK.

1.6 Reflecting the commission from the previous government, the report considers how competition has changed on a cross-economy basis. Although we look at trends in our key indicators at a broad industry level, the scope and focus of this exercise does not lend itself to the identification of issues holding back competition in particular markets or sectors, or corresponding policy interventions.

1.7 Nonetheless, we have gone further in this edition to analyse what lies behind the trends in key cross-economy indicators of competition and their broad implications for policy. We find, for example, that the rise in markups has been driven principally by firms that are older, larger and had higher pre-existing markups. This is consistent with our findings that there has been a reduction in business dynamism, with established firms better able to sustain their position over time, and new entrants less successful than they used to be in displacing incumbent firms. We also find that technological changes have made fixed costs such as R&D, software and branding more important to firms' ability to compete effectively. Together, these findings help to indicate a number of areas on which policy might focus in order to sustain and improve competitive conditions in the UK, to support growth and productivity. In particular, they highlight:

a) The importance of early analysis of markets subject to rapid technological change, and the consideration of measures to prevent the pre-existing power of incumbent firms being further entrenched. Of particular relevance in this context is the CMA's work in digital markets, and the new ex-ante powers it has acquired to maximise opportunities for sustained innovation in these critical economic sectors. The CMA has also set out as part of its review of AI Foundation Models (CMA, 2024) how the benefits flowing from these fast-developing technologies depend on an environment of fair, open and effective competition, and the importance of any future regulatory intervention taking this into account.

b) The importance of understanding the barriers that prevent smaller, younger, innovative firms from competing effectively with larger high-markup incumbents and taking corresponding measures to address these to support greater business dynamism – for example, through improving knowledge diffusion across the economy, or ensuring more open access to key inputs or technologies. Looking ahead, the CMA will look to improve the evidence base and inform policy in this area through the work programme of its Microeconomic Unit (see below).

c) The case for continued effective merger control and competition enforcement in keeping market power in check. This is likely to be especially important in an economic environment where technological change disproportionately benefits larger incumbent firms.

1.8 For the first time, the State of Competition report has been produced by the CMA's Microeconomics Unit. Established in Darlington in 2022, the Unit provides research, analysis and expertise on competition, consumer outcomes, innovation, productivity and supply-side reforms, with the objective of informing and supporting the CMA's own work, and that of wider government. Reflecting this purpose, the Unit's forthcoming work in this area, and more broadly, will be informed and shaped by engagement with policymakers, and their perspectives on the evidence and analysis that would best support the government's policy priorities.

1.9 In particular, the Unit has launched a programme of work focused on growth and industrial strategy. Building on some of the findings in this report, this will include analysis of barriers to the spread of new technology across the economy; market power and resilience in supply chains; policy levers to support business dynamism; and the role of competition in driving and directing investment towards productive uses. The Unit's forthcoming work is set out in paragraph 1.45.

Has competition in the UK become stronger or weaker over time?

1.10 The strength of competition is not directly observable but must instead be inferred by interpreting relevant indicators. We report three sets of indicators of the strength of competition over time: cost markups, static concentration measures, and measures of business dynamism. Our analysis shows that:

a) Cost markups, economists' preferred measure of aggregate market power, have risen by around 10% in Great Britain over the past 25 years. This is an indication that competition across the economy may have weakened. The figure is, however, lower than those found in some previous UK studies, and lower than many other advanced economies, including the US.

b) Concentration across a range of measures has remained relatively stable. This stands in contrast to the US, where some studies indicate a significant rise in concentration across the economy. In other European countries, the picture is mixed.

c) Business dynamism has fallen over the past 25 years – another indication of weakening competition. Firm entry and exit rates have declined across most sectors. The job reallocation rate – the share of employment in an industry that changes hands from one year to the next – has declined. At the top of most industries, the largest firms are more likely to keep their position over multiple years.

Cost markups

1.11 Cost markups are our preferred measure of competition at a whole-economy level because they most closely reflect the concept of market power: that is, the extent to which firms can sustain prices above (and output below) competitive levels. Over the long run, higher levels of market power usually go hand in hand with lower levels of competition. Cost markups in particular are estimates of the difference between the price a firm charges and its marginal cost of production.

1.12 Since 1997, according to our baseline estimate shown in Figure 1, average markups in Great Britain have risen by about 10%.[1] Using an alternative data source that includes Northern Ireland, the trend remains similar for the whole of the UK. This means that the average difference between prices and marginal costs is now bigger than at the turn of the century.

1.13 Our baseline estimate lies at the lower end of existing studies, but we believe it is based on more robust methods and therefore better represents trends in Great Britain. Other approaches produce estimates of between 9% and 40%.

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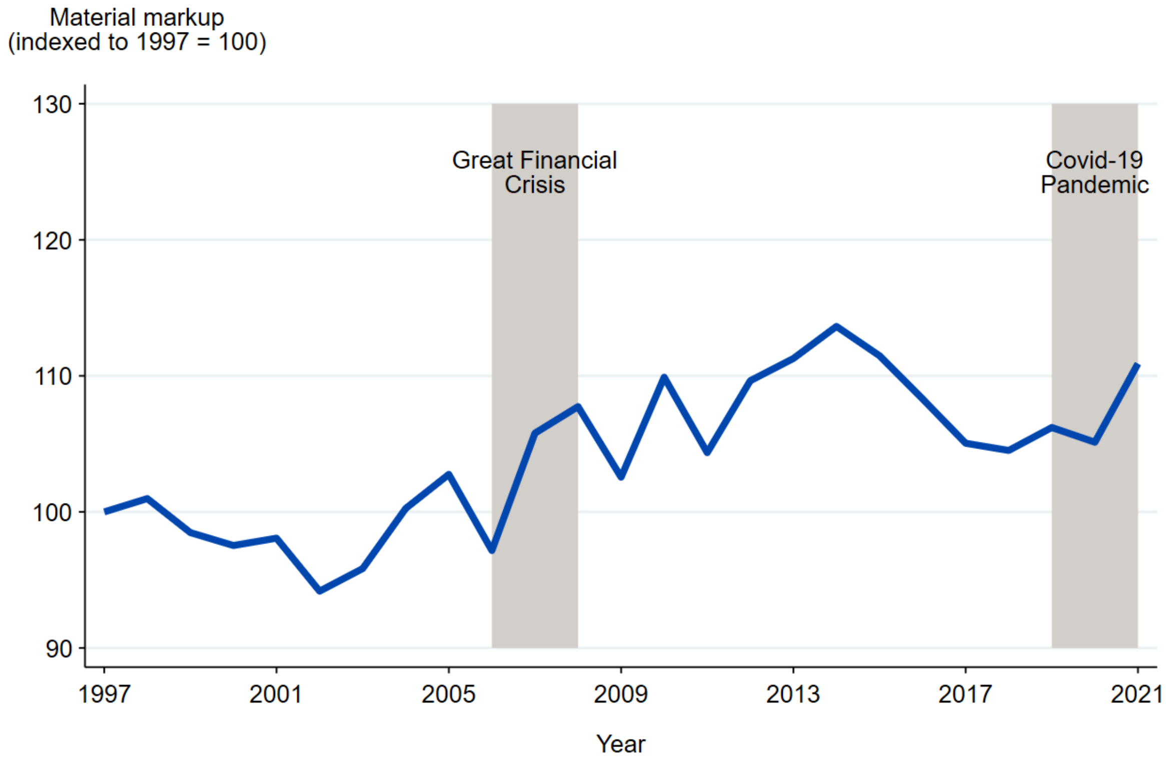
[1] Since some of the Northern Ireland business datasets are not available in the Office for National Statistics' Secure Research Service, our baseline cost markups are Great Britain-only, in contrast to our other measures of competition across the economy. However, we produce supplementary markup estimates using a different dataset that includes Northern Ireland and find very similar trends. We also aim to provide a data-only release of the cost markup series once data access has been resolved.

Figure 1: Average markups in GB have risen since 1997

Economy-wide average markup estimates. Baseline measure: Ordinary Least Square (OLS) estimation of a translog production function. Firm-level estimates are aggregated weighting by turnover. Data from the Annual Respondent Database X 1997-2020 and Annual Business Survey 2021 (GB only)



Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021).

Concentration

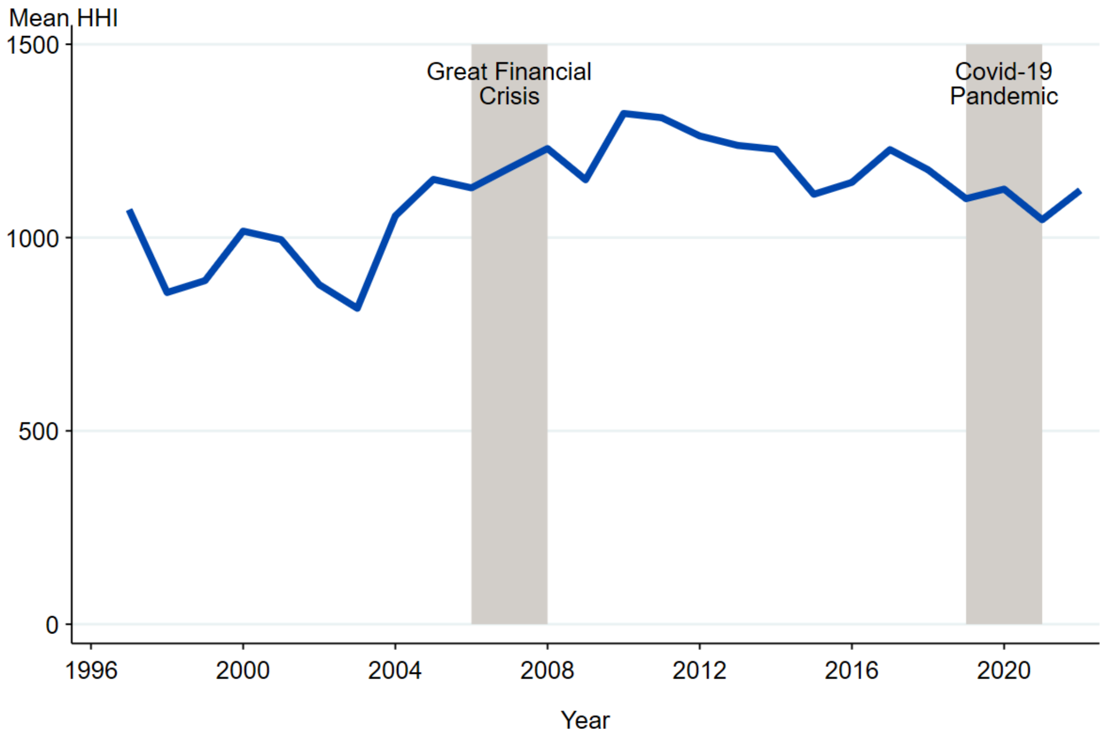
1.14 Concentration measures the extent to which industries are dominated by a small number of large firms. Higher levels of concentration mean that a smaller number of firms control a larger share of the market, which may lead to weaker competitive pressures and greater market power. However, taken in isolation, concentration is, at best, an imperfect measure of competition. Even in concentrated markets, competition can sometimes be fierce, and substitute products or potential entrants may sometimes constrain incumbents.[2]

[2] In its analysis of individual markets, the CMA often uses indicators of market concentration as part of a competitive assessment. In these cases, concentration indicators are generally used alongside a range of other qualitative and quantitative data and applied at a granular level (such as individual markets, rather than broad

1.15 The increase in markups seen since 1997 does not appear to have gone hand in hand with an increase in concentration within industries. Across a range of measures, concentration increased during the mid-late 2000s, then fell slightly. The latest data (2022) shows that it stands at similar levels to 1997 (Figure 2). Some measures indicate concentration has fallen in manufacturing, and risen in wholesale and retail, but overall trends are similar across industry sectors.

Figure 2: The average concentration has remained roughly stable after the Great Financial Crisis

Mean Herfindahl-Hirschman Index (HHI), our baseline concentration measure. HHIs calculated at four-digit Standard Industrial Classification (SIC) level and aggregated using industry turnover as weight. Data from the Business Structure Database (BSD) 1997 – 2022



Herfindahl Hirschman Index calculated at 4-digit Standard Industrial Classification (SIC) level for each year. Weighted mean using industry turnover as weight. All SIC sectors included. Data from the *Business Structure Database* (1997-2022).

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industries). The cross-economy nature of the analysis in this report, and the limited availability of routinely collected data at the level of individual markets, reduces the interpretive value of concentration measures in this context.

Business dynamism

1.16 In competitive markets, we expect to see firms entering and leaving, jostling for market share, and resources being reallocated to more productive uses. This dynamism is a key channel through which competition drives productivity.

1.17 We measure business dynamism in four ways:

a) firm entry and exit relative to the total number of firms in an industry;

b) the share of employment in an industry that changes hands from one year to the next (the so-called “job reallocation rate”);

c) the extent to which the same largest firms remain at the top of each industry across multiple years; and

d) the employment and turnover shares of young firms.

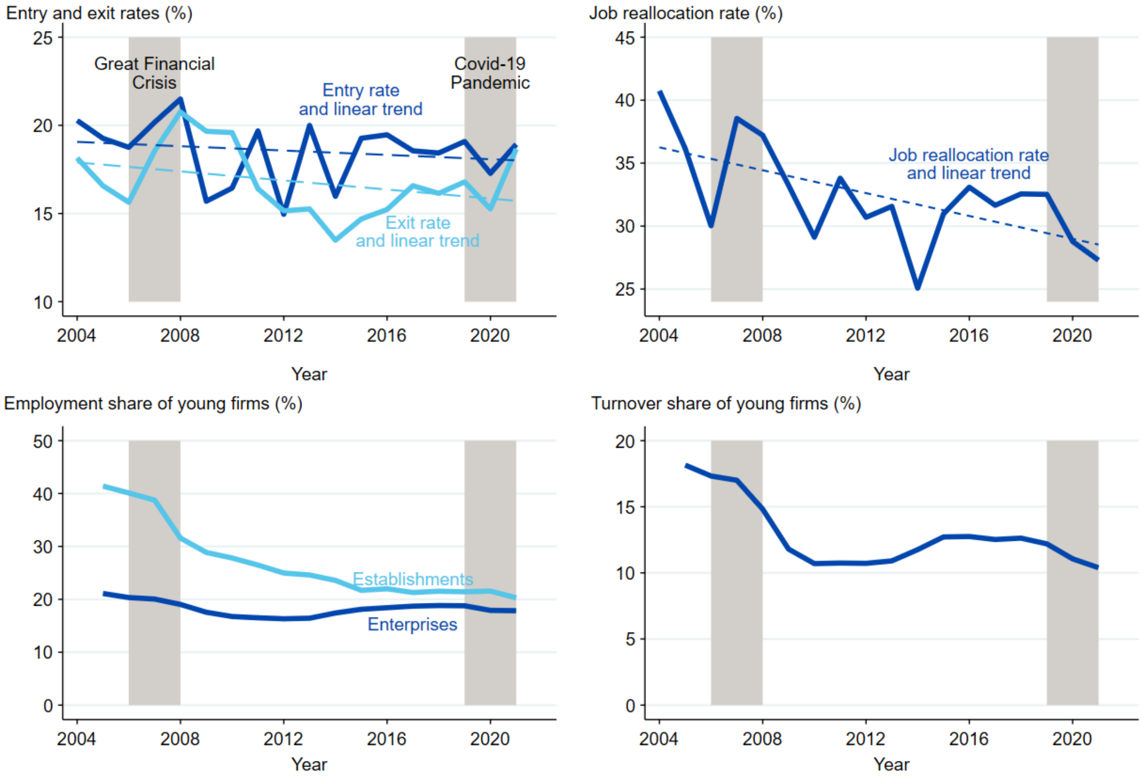
1.18 Across all measures, business dynamism has fallen in the UK economy over the past 25 years. Figure 3 shows the fall in the firm entry and exit rates, the job reallocation rate and the employment and turnover shares from 2004 onwards.

1.19 Dynamism has declined both at the top of the average industry, with industry leaders more likely to remain in place over multiple years, and at the bottom, with young firms accounting for a smaller share of turnover and employment.

1.20 The fall in business dynamism is remarkably uniform across the economy, with only transportation and storage and wholesale and retail showing increasing business dynamism on some measures.

Figure 3: Business dynamism has declined since 2004

Whole economy entry, exit and job reallocation rates and employment and turnover share of young firms. Employment shares shown both for individual establishments and firms (enterprises). Data from the Longitudinal Business Database, 2004-2021



Young firms are less than 5 years old. Age of enterprises and establishments estimated using the year of first appearance on the *Longitudinal Business Database*. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2004-2021).

Understanding changes in competition

1.21 The aim of this report is not simply to document changes in competition indicators across the UK economy, but to explain what lies behind these changes - particularly to cost markups, our preferred measure of market power. We have carried out substantial analysis to understand the underlying drivers of markup trends, and what the results could indicate.

What sorts of firms and sectors are driving markups, and what does this tell us about competition?

1.22 **The increase in markups has been driven predominantly by firms that already have the largest markups**: markups have risen far more (up to three times as much by some measures) among firms at the top of the distribution than they have elsewhere. This indicates that the most successful firms have entrenched their positions over time, rather than being displaced, and the gap between them and other businesses has grown.

1.23 **The dispersion of markups has grown**. This indicates that productivity improvements may not be spreading as quickly through the economy, either via learning and diffusion, or through the exit of low-productivity firms.

1.24 **After controlling for firm characteristics, firms with high markups are on average older and bigger.** Taken together with the two observations above, this supports the conclusion – also evident in our business dynamism indicators – that there has been a reduction in dynamism in the UK economy over the last 25 years.

1.25 **Markup trends have been driven principally by "within-industry" rises.** The overall markup figure is a sales-weighted average figure. It can therefore increase for two broad reasons: because markups increase for a certain firm or within a certain industry, or because sales shift towards high-markup firms or industries. Sales reallocation is more indicative of competition working well than within-firm or within-industry markup rises. We see that markups have been mostly driven by within-industry increases, pointing to a reduction in competitive intensity.

1.26 **Service industries, particularly administrative and support services and professional services, have seen their markups increase the most.** Other sectors, such as manufacturing, have not seen their markups rise over the past 25 years. This may reflect to an extent the changing cost structure of services, and the growing importance of intangible capital in this sector (see below).

1.27 **Firms in sectors that are exposed to international trade tend to have lower markups**, indicating that international competition acts as a constraint on domestic market power.

1.28 **Markups tend to be higher the further upstream the industry is along supply chains** (that is, the further away the industry is from final consumers). Further work to understand how these "upstream" markups (and the associated economic inefficiencies) propagate through the economy is an area that the Microeconomics Unit is prioritising for further research.

1.29 **Ownership linkages among firms both within and across industries are widespread.** We find evidence of substantial within-industry and cross-industry ownership networks, with finance and overseas entities often serving as crucial nodes in the network. These can matter for market power and consumer outcomes if commonly owned, or otherwise connected, firms compete less intensively than standalone firms. Building on the results in this report, the

Microeconomics Unit will carry out further research to understand the extent and impact of these linkages.

Why have markups risen over time, and what does this mean for policy?

1.30 As discussed above, rising markups over recent decades have been seen across many advanced economies. Broadly, the academic literature distinguishes between two explanations for this.

The technology explanation

1.31 According to this explanation, the change in the way we produce goods and services, and therefore in the cost structure of firms, has driven the observed rise in cost markups. In particular, the role of “intangible capital” has become increasingly important, meaning firms need to invest upfront in fixed costs such as R&D, software and branding to compete effectively. However, this investment then makes it cheaper to produce each additional unit (for example, because an increasing share of consumer goods consists of software components, which can be reproduced at zero cost).

1.32 This explanation is sometimes interpreted as more “benign” because it explains rising cost markups (and concentration) as a consequence of structural changes that have led to lower marginal costs and higher fixed costs, rather than anti-competitive conduct driving prices above competitive levels. However, despite the many benefits of intangibles for productivity, an economy in which these are more important to production might also be an economy with more barriers to entry: for example, as a result of high fixed costs, intellectual property protection, or unequal access to data. It may also lead to an environment where firms have greater means and opportunity to entrench and exploit their strong positions, which might allow markups to rise due to weakened competition.

1.33 In short, a technology-driven rise in cost markups may still be consistent with lower levels of competitive pressure and dynamism, and an environment that is more conducive to the growth of market power.

The “pricing power” explanation

1.34 According to this explanation, markups have risen because prices are being driven further above competitive levels due to firms being able to extend or more effectively exercise their market power. This growth in market power might have come about, for example, through M&A activity, or through practices by incumbent firms that inhibit the entry and expansion of potential rivals.

1.35 Effective merger control and competition enforcement should in principle provide an important check on the growth of markups via this channel, by preventing firms gaining a position of market power through acquiring their competitors, and by tackling abuses of dominant market positions.

1.36 In contrast to the US, where studies have shown that M&A activity has materially contributed to rising markups, there is no evidence in the UK to indicate that markups have been driven by M&A activity, or ineffective competition enforcement.

1.37 The technology and "pricing power" explanations are not mutually exclusive: for instance, the growth of intangible capital may both make it easier to produce new goods faster and more cheaply, and better enable firms to erect barriers against new entrants.

1.38 We tentatively conclude that, overall, the technology explanation plays a more significant role in driving markup trends in the UK. This is because markups are highly correlated with returns to scale, but less so with the proportion of sales revenue that firms retain as profit. However, both explanations are likely to be relevant to differing extents in different sectors of the economy, and both pose challenges for competition policy and enforcement.

Beyond cross-economy averages: competition at the industry level

1.39 In line with previous editions, this report brings together evidence on competition and market power at the whole-economy level, rather than looking to identify particular markets or sectors where competition is especially weak. This raises the question of whether it is possible to "drill down" into our results and evaluate these same indicators at the level of individual industries and markets.

1.40 Two principal difficulties arise from disaggregating in this way. The first is in matching the data up to individual markets: even our narrowest measures of industries are not always a good match for the actual markets in which firms compete. Data limitations, together with necessary adjustments made to deal with 'outlier' firms (see paragraphs [2.14-2.15]), also prevent us from applying the analysis carried out in this report to look specifically at digital markets and the impact of the rise of large tech companies on competition. The CMA has, however, considered this question extensively through other work.[3]

[3] See, for example, the Online platforms and digital advertising market study (CMA, 2020), the report of the Digital Markets taskforce (CMA, 2021), the Mobile ecosystems market study (CMA, 2022), the Trends in Digital Markets report (CMA, 2023) and Cloud services market investigation (CMA, 2024).

1.41 Second, complexity and variation in production and supply can make comparisons between industries hard to interpret. Just as we need to consider changing cost structure across the economy to interpret aggregate markup trends over time, so we would need to account for this – and other features of structure and conduct – in different industries to draw meaningful conclusions from comparisons of cost markups and other competition indicators.

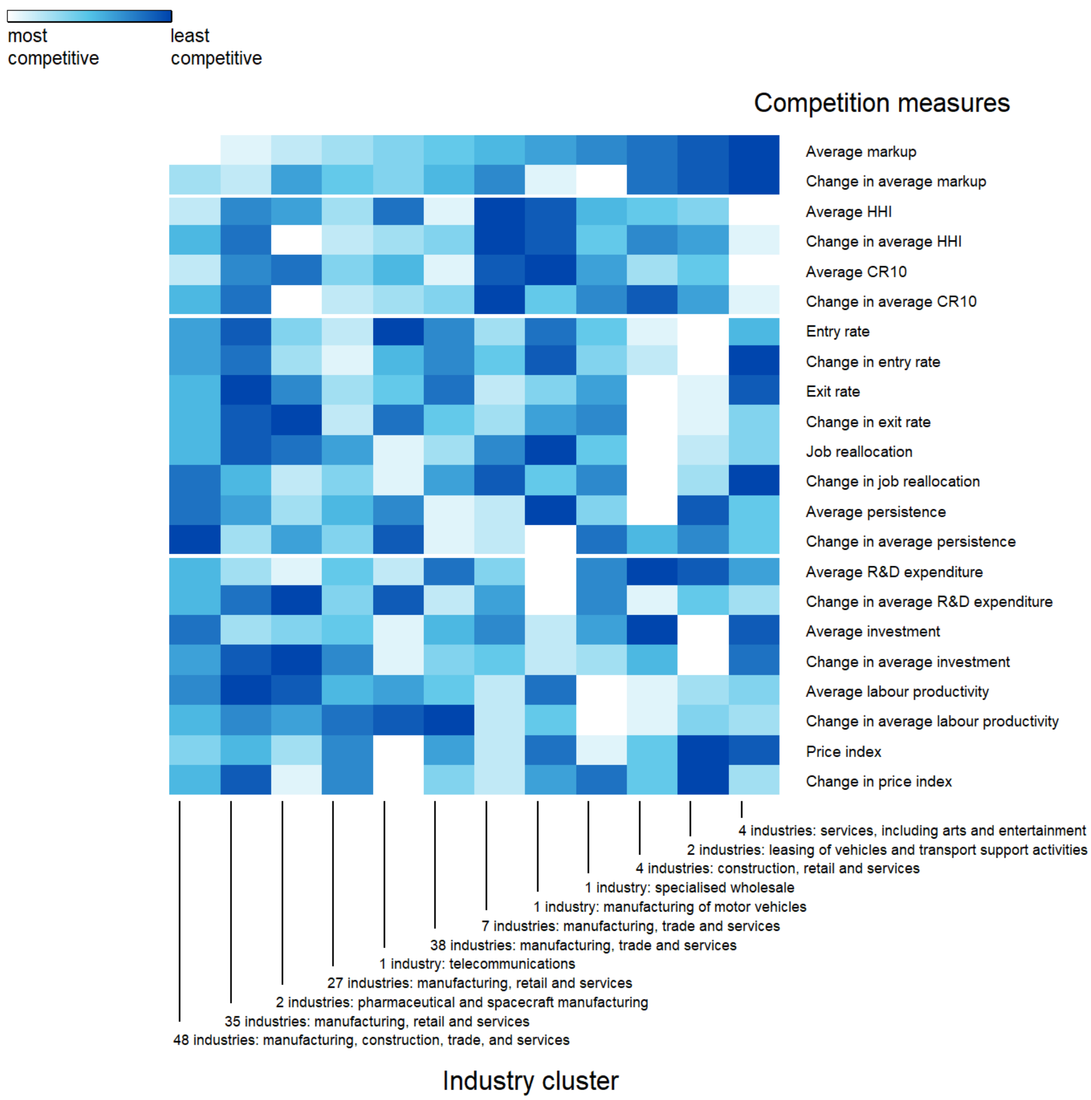
1.42 However, in an effort to bring our analysis of different indicators together, and apply it at an industry level, we have clustered industries that behave similarly across the various measures used in the report, including markups, concentration, dynamism, and selected "outcomes" that might be expected from effective competition (R&D, investment, productivity and prices). Where many indicators are pointing "in the same direction", this may give cause for comfort, or reason to look further into the state of competition in a particular industry.

1.43 We find the economy can be divided into twelve clusters, based on the nature of competition in those industries (Figure 4). The cluster with the highest markups consists of four industries: namely, creative arts and entertainment; temporary employment activities; information services; and the organisation of conventions and trade shows. In addition to high markups, these industries have also seen the largest increase in markups, and low or declining entry, exit and reallocation rates. Despite this, concentration in these industries is neither particularly high nor increasing, indicating that concentration measures alone are not a good guide to an industry's competitiveness.

Figure 4: Industries vary widely in how firms compete

Heatmap from a k-means clustering exercise (see [Paragraphs 7.44-7.46]. Clusters are ranked by their average markup, from lowest (left hand side, lightest colour) to highest (right hand side, darkest colour). Across all variables, cell colours in the heatmap show how competitive a cluster is on each measure on average, again ranging from light (most competitive) to dark (least competitive). Calculated at the three-digit Standard Industrial Classification (SIC) level.

Data from Annual Respondents Database X (ARDx) 1997-2020, Annual Business Database 2021, Business Enterprise Research and Development survey (BERD) 1995-2017, Business Structure Database (BSD) 1997-2022, Industry level deflators by Office for National Statistics 1997-2023, Longitudinal Business Database (LBD) 1997-2021. GB only



Each cell gives the intensity of competition in each selected measure for a given cluster of 3-digit Standard Industrial Classification (SIC) industries. Darker shades indicate less competition. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to 2005-2017 and excluding SIC sectors: A, B, D, E, K, L, O, P, Q, T, U. Markups are calculated following our baseline approach described in the report. Clusters are ranked by their average markup over that period. Data are 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).

Further work

1.44 This exercise underscores the importance of complementing a whole-economy view of competition and market power with more focused analysis that can account for the complexity of how firms and consumers interact in specific industries and markets.

1.45 With this in mind, the Microeconomics Unit's upcoming work will build on the findings of this report, and focus in particular on areas of close relevance to the government's economic policy priorities. This will include:

a) A report analysing past growth-focused and industrial policies, and other evidence, to shed light on policy levers to increase business dynamism and harness the productivity contributions of "superstar" firms (high productivity, high market share firms that dominate their industries).

b) A review of the evidence on the role of competition in driving and directing investment towards productive uses, and subsequent empirical analysis to address any evidence gaps identified.

c) Work that builds on some of the potential policy implications of this report, including on the factors affecting the diffusion and adoption of technology across different industries.

d) A report analysing the results of the latest Consumer Detriment Survey and other evidence to understand how consumers experience the economy, and where competition is not working for them.

e) Work that fills in a number of the data and research gaps identified in this report around local competition; ownership structures and consumer outcomes; the characteristics of the most productive and innovative firms; and the extent of weak competition in "upstream" sectors, and its impact on downstream markets.

f) More focused work on how competition is working in particular industries and sectors, to complement the cross-economy findings in this report.

2 Market power in the UK

2.1 Overall, cost markups, our most direct measure of aggregate market power, have increased by about 9% to 40% in Great Britain over the past twenty-five years. Our best estimate of 10% lies at the lower end of this range and is lower than those found in some previous studies.

2.2 The increase in markups has predominantly been driven by older, larger firms with the largest markups, and by the services sector. Rising markups within industries and reallocation between high- and low-markup industries have both played a role. However, rising markups within industries have been quantitatively more important in recent decades.

Measuring market power

2.3 When many firms compete in the same market, competitive pressures push prices down to where firms can just cover the cost of producing the last unit (the so-called marginal cost). By contrast, a firm with market power can raise prices by restricting output, and therefore can often price significantly above marginal cost.

2.4 Therefore, the extent to which firms raise prices above marginal cost is a good measure of the market power they hold in their output market. We call the difference between price and marginal cost the cost markup, or markup for short.

2.5 Markups are a better measure of market power than traditional market concentration measures, because competition can be fierce even in markets with few firms (for instance, if their products are undifferentiated) or sluggish even in markets with many firms (for instance, if consumers do not travel far so that each firm has a local monopoly).

2.6 Market power is of course not the only reason price may be above marginal cost. Firms may also need to cover their fixed costs. Fixed costs refer to any costs incurred regardless of the quantity produced, such as administrative overheads or the cost of leasing or building a factory. Therefore, a rise in measured markups may reflect either a rise in market power, a rise in fixed costs, or a combination of the two.

2.7 Finally, other market failures that stop firms from expanding their output (such as financial constraints, or input market frictions) may also lead to a divergence between price and marginal cost. Care is therefore needed when interpreting markup trends in times of economic turmoil such as the pandemic, when such disruptions may be particularly acute.

2.8 To measure markups, we need a measure of prices and of marginal costs. While we can in principle observe prices, we usually do not observe marginal costs directly.

2.9 Therefore, we infer costs by estimating the production function of firms across the economy: how much output they produce, and what combination of inputs they use to produce it. We call this the “production function approach”.

2.10 To ensure we are measuring market power and not some other market friction, we also need to assume that firms can adjust at least one of their inputs easily. We follow previous studies and use material inputs for this purpose. Labour inputs are the other option frequently used in previous academic research. Our previous report on labour market power (CMA, 2024) finds evidence of labour market power across many UK firms. Therefore, we opt for material inputs instead.

2.11 The markup for each firm then depends on two components: the materials share of revenue and the elasticity of revenue with respect to material inputs. The materials share of revenue measures the fraction of revenue that is used to pay for material input costs. The elasticity of revenue with respect to material input captures how responsive revenue is to a small increase in material inputs used.

2.12 We observe the former directly in Great Britain’s structural business survey, the Annual Business Survey (ABS), and estimate the latter by assuming firms in each two-digit Standard Industrial Classification (SIC) industry use the same production technology. We provide more details about the methods and data sources we use in the appendix.

2.13 The production function approach is not only widely used in the literature, but also makes less stringent assumptions about production technologies than the alternative cost-share approach used for markup estimation in the CMA’s previous State of UK Competition report (CMA, 2022).

2.14 To prevent large measurement errors from influencing the results, and to ensure comparability with other studies, across time and between countries, we remove “outliers” from our analysis of markups within each industry: that is, firms whose cost shares or markups put them at the very extremes of the firm distribution.

2.15 Therefore, the analysis is unlikely fully to reflect the growth of the largest digital tech companies, which may be excluded due to their cost shares or markups exceeding this threshold. The impact of the growth of digital markets, and of the largest digital firms, on competition in the UK has been considered extensively in other CMA work, including the Online platforms and digital advertising market study (CMA, 2020), the report of the Digital Markets taskforce (CMA, 2021), the Mobile ecosystems market study (CMA, 2022), the Trends in Digital Markets report (CMA, 2023) and Cloud services market investigation (CMA, 2024).

2.16 Production function estimation methods are still an active area of research themselves, with critics suggesting refinements or favouring other approaches (e.g. Gandhi, Navarro, Rivers, 2019; Bond, Hashemi, Kaplan, Zoch, 2021; Kirov, Mengano, Traina, 2023).

2.17 Because Northern Ireland runs its own structural business survey, the Annual Business Inquiry, which is not available in the Office for National Statistics' Secure Research Service, we are not able to include baseline Northern Ireland markup estimates in this report, in contrast to our other measures of competition across the economy. However, our supplementary cost share markup estimates in appendix figure E.1 use a different dataset that includes Northern Ireland and find very similar trends.

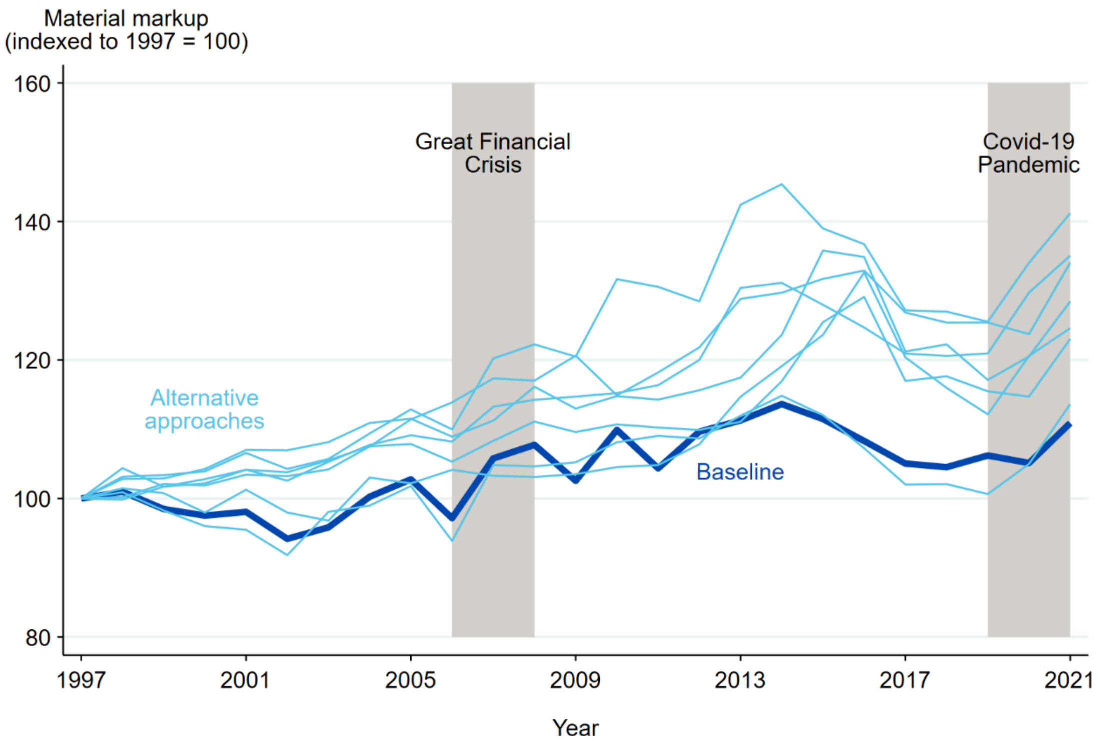
UK markups have increased in recent decades

2.18 We find that average markups across the GB economy have risen around 10% over the past two decades, according to our best estimate. Figure 5 shows that depending on the methodology and weighting used, the cumulative rise may have been between 10% and 40% of the initial 1997 level. By most measures, markups peaked in the mid-2010s before falling for a few years pre-Covid. Aggregate markups have risen again during Covid and remain above the initial 1997 level.

2.19 Other researchers have found increases of similar magnitudes, with the consensus estimates for the period from 1997 to 2015 in the 9-25% range. Aquilante, Chowla, Dacic, Haldane, Masolo, Schneider, Seneca and Tatomir (2019) find an increase in average markups of 23%. De Loecker, Obermeier and Van Reenen (2022) similarly find that the aggregate markup has increased by 24%. Hwang, Savagar and Kariel (2022) document rising aggregate markups between 1998 and 2014, with a temporary plateau around 2008. Black (2022) finds that average markups have increased by 9% percent in the UK between 1997 and 2019.

Figure 5: Average markups in GB have risen since 1997

Economy-wide average markup estimates. Baseline measure: Ordinary Least Square (OLS) estimation of a translog production function with materials as flexible input. Firm-level estimates are aggregated and weighted by turnover. Data from Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey (ABS) 2021. GB only



Markups are calculated following our baseline approach described in the report. Alternative approaches include different production functions, different aggregation weights and control function estimation methods. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021).

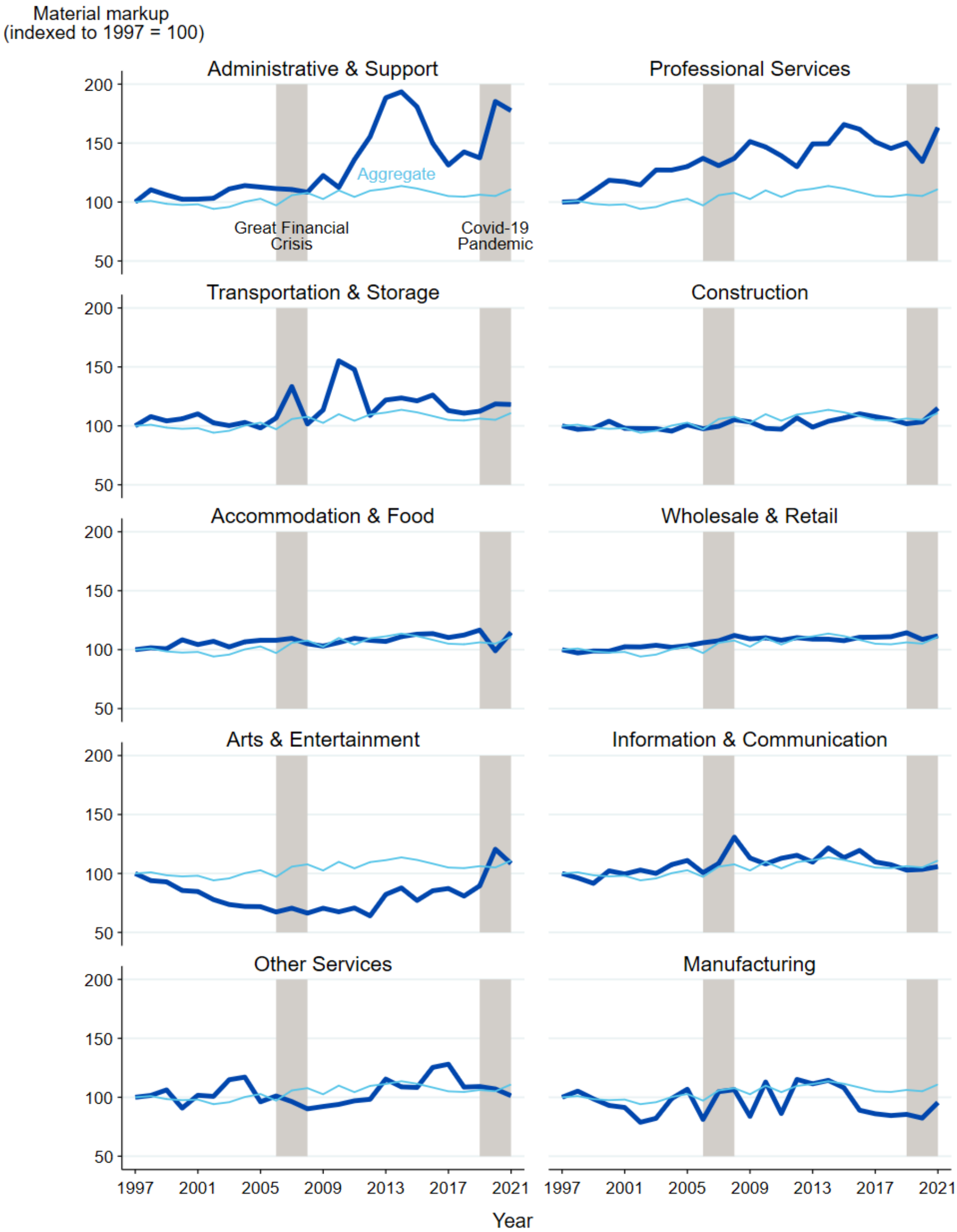
Services have been the major contributor to the rise in markups

2.20 The average rise in markups has been driven predominantly by the service sector. Markups in administrative and support services, professional, technical, and scientific services, and arts and entertainment (in more recent years) have increased particularly rapidly. In contrast, markups in manufacturing, construction as well as accommodation and food services have seen milder increases in the last two decades.

2.21 Figure 6 compares the rise in sectoral markups to the whole-economy average. It illustrates that the rise in markups varies widely. Markups have been rising in professional services over the entire time period, whereas the rise in administrative and support services and arts and entertainment only begins after the Great Financial Crisis. Manufacturing markups have not risen over the past twenty-five years.

Figure 6: Some service sectors have experienced the steepest rise in average markups

Average markups in Standard Industrial Classification (SIC) sectors. Ordinary Least Square (OLS) estimation of a Translog production function with materials as flexible input. Firm-level estimates are aggregated weighting by turnover. Data from Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey (ABS) 2021. GB only



Markups are calculated following our baseline approach described in the report. Industries are ranked by the highest index in 2021. Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Data from the *Annual Respondents Database X* (1997-2020) and the *Annual Business Survey* (2021).

2.22 Figure 7 shows the sectoral contributions to the whole-economy average markup. This contribution depends on the sectoral markup changes, but also on their relative markup levels and the size of each sector.

Figure 7: Industries such as administrative and support, and transportation and storage have contributed to the increase in the average markup, while construction and information and communications have dampened it

Annual sectoral contribution to average markup. Ordinary Least Square (OLS) estimation of a Translog production function with materials as flexible input. Firm-level markups are aggregated weighting by turnover. Data from Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey (ABS) 2021. GB only

Markups are calculated following our baseline approach described in the report. Industries ordered by largest contribution to the aggregate markup between 2019 - 2021. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997 - 2020) and *Annual Business Survey* (2021).

2.23 From 2010, administrative and support services (which includes rental and leasing, building services and employment services) have increasingly contributed to rising overall markups. Transport and storage and accommodation and food services have contributed to increasing average markups throughout. Arts and entertainment have lowered the average markup in most years but have raised it since the Covid-19 pandemic. Manufacturing and wholesale and retail both display cyclical patterns of markups over the period.

Reallocation has played a relatively minor role in the rise of markups

2.24 The whole-economy markup represents an average of each individual firm's contribution. To obtain this average, each firm's markup is weighted by their total turnover, which measures how important each firm is to aggregate outcomes. This means the average markup can change both when individual firms change their markups and when turnover is reallocated from one firm to another.

2.25 In this section, we investigate different ways of splitting up the markup trend to better understand where it comes from. We generally find that reallocation plays some role, but that "within" changes (increases in the markup at a given firm or industry) are quantitatively more important.

2.26 While both reallocation of turnover between firms (changes in the weights) and markup changes at a given firm can increase the average markup, they have different implications for what factors are driving the increase.

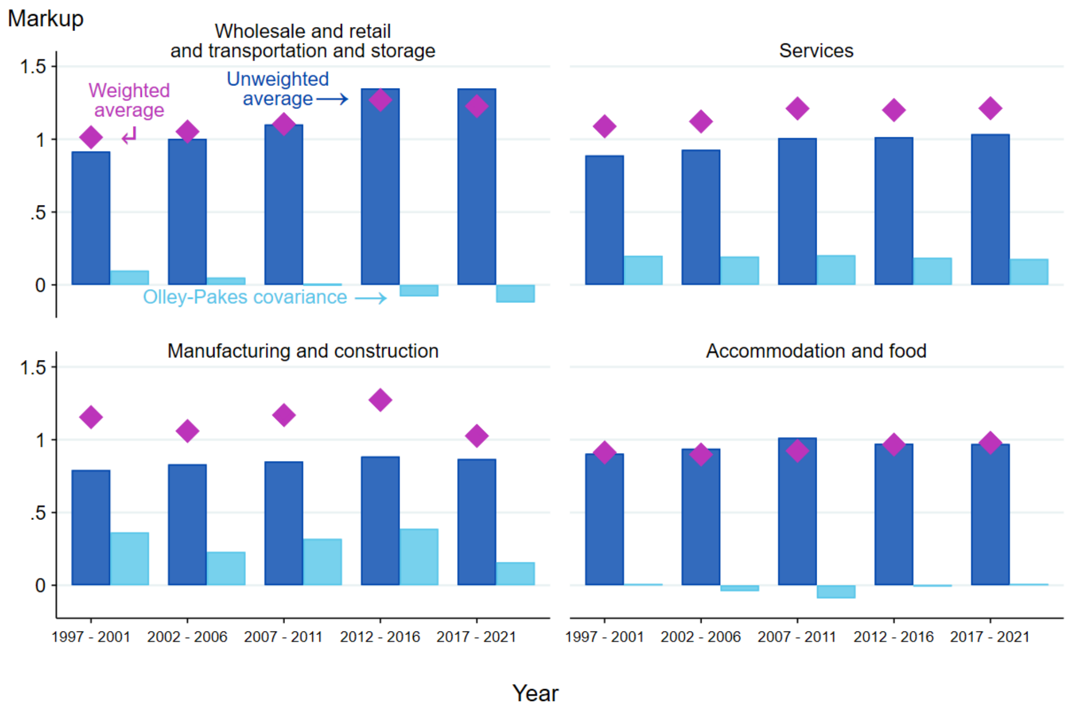
2.27 Because a reallocation-driven markup increase signals that consumers are moving towards high-markup firms (presumably because they like their products), it points towards a pro-competitive, efficiency-enhancing technology explanation. A rising "within" contribution on the other hand may reflect firms raising prices on locked-in consumers and is therefore consistent with not only a technology story but also a "pricing power" explanation.

2.28 Decomposing the weighted average can be done in a variety of ways. The simplest way to do so splits the weighted average into an unweighted average (within-firm increases) and a term that captures the degree to which high-markup firms have larger market shares. The latter is called the Olley-Pakes covariance term after the initial proponents of this decomposition method Olley and Pakes, 1996).

2.29 Figure 8 shows that in Great Britain, most of the increase in the average markup is due to changes in the unweighted average, although reallocation (measured as the Olley-Pakes covariance term) plays a part as well. Only in manufacturing and construction, and to some extent services, does reallocation play a substantial role in the markup trends.

Figure 8: In most sectors, reallocation plays a minor role in the rise of markups

High-level sectoral markup Olley-Pakes decompositions: weighted average (purple diamond) overall increase is decomposed into the unweighted average (dark blue bar) and the Olley-Pakes covariance term (light blue bar). Estimates are averaged over sub-periods. Markups computed using Ordinary Least Square (OLS) estimation of a Translog production function with materials as flexible input. Data from the Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey (ABS) 2021. GB only



Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Olley-Pakes decompositions averaged over sub-periods. Industries are ranked by their weighted markup in the period 2017-2021. Data from the *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021).

2.30 We can go even further and divide changes in the average markup into three components, adapting a method proposed by De Loecker, Eeckhout and Unger (2020).

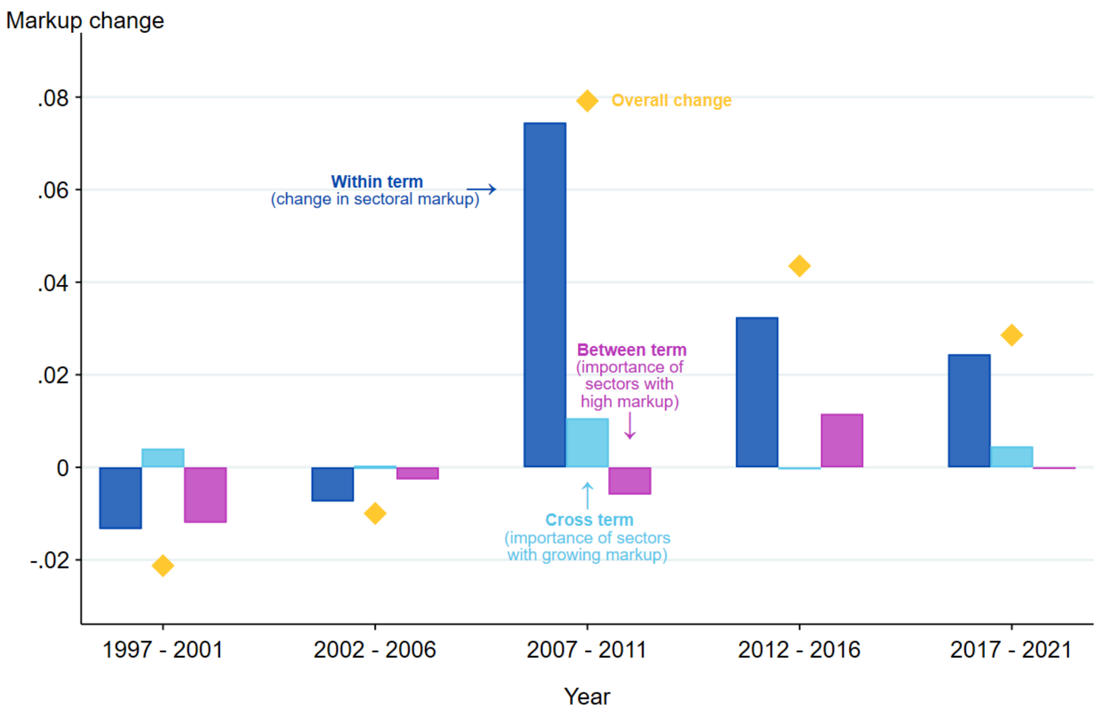
2.31 The first component measures within-sector rises in markups (what we call the “within” component). The second measures the changing importance of sectors with rising markups (what we call the “cross” component). The third measures the changing importance of sectors with high markups (what we call the “between” component).

2.32 The relative contribution of these three terms gives us some clues as to what might be behind the rise in markups. For instance, if the intensity of competition is falling, we might expect to see higher markups within sectors. If the basic structure of the economy is changing, this could be reflected in a rising “between” contribution (which may raise or lower average markups, depending on the sectors involved). A rise in so-called “superstar” firms (innovative, high-performing firms with large market shares) may be reflected in a higher correlation between markups and turnover and therefore a higher “cross” term.

2.33 Figure 9 breaks down the average change in the markup into these three terms, for five periods of equal length between 1997 and 2021.

Figure 9: Most of the increase in the average markup is due to sectoral markups being higher, not to reallocation of economic activity

Decomposition of the change in aggregate markup in variation due to sectoral markups being higher (within component) and reallocation of economic activity (between and cross component). The decomposition follows the one proposed in De Loecker, Eeckhout and Unger (2020). Data from Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey 2021. GB only



Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Sectoral decomposition following De Loecker,Eeckhout, and Unger (2020), averaged over sub-periods. Data from *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021).

2.34 Within-sector changes in markups have contributed the majority share of the overall rise in markups (the “within” term). Additionally, sales have shifted towards industries with growing markups (the “cross” term) which has increased the average markup. Finally, in the first decade of the century, the sales share of high-markup industries has pulled the average markup down (the “between” term). However, this relationship has weakened over time and even reversed, suggesting that markups and sales shares are now increasingly correlated.

2.35 Together, these results support a pricing power explanation of rising markups, as most of the increase over time has come predominantly from “within” changes rather than from reallocation of turnover between firms.

Firms with higher markups are bigger, older, and more profitable

2.36 This section sheds additional light on which types of firms are behind the rise in markups. The rise in average markups is predominantly driven by firms with already high markups. High-markup firms are on average older, larger, more profitable and have a higher labour share than low-markup firms in the same industry.

2.37 Figure 10 plots average markups over time alongside markups at different points of the markup distribution. This allows us to compare how markups have changed for firms with low, medium and high markups at the beginning of each year.

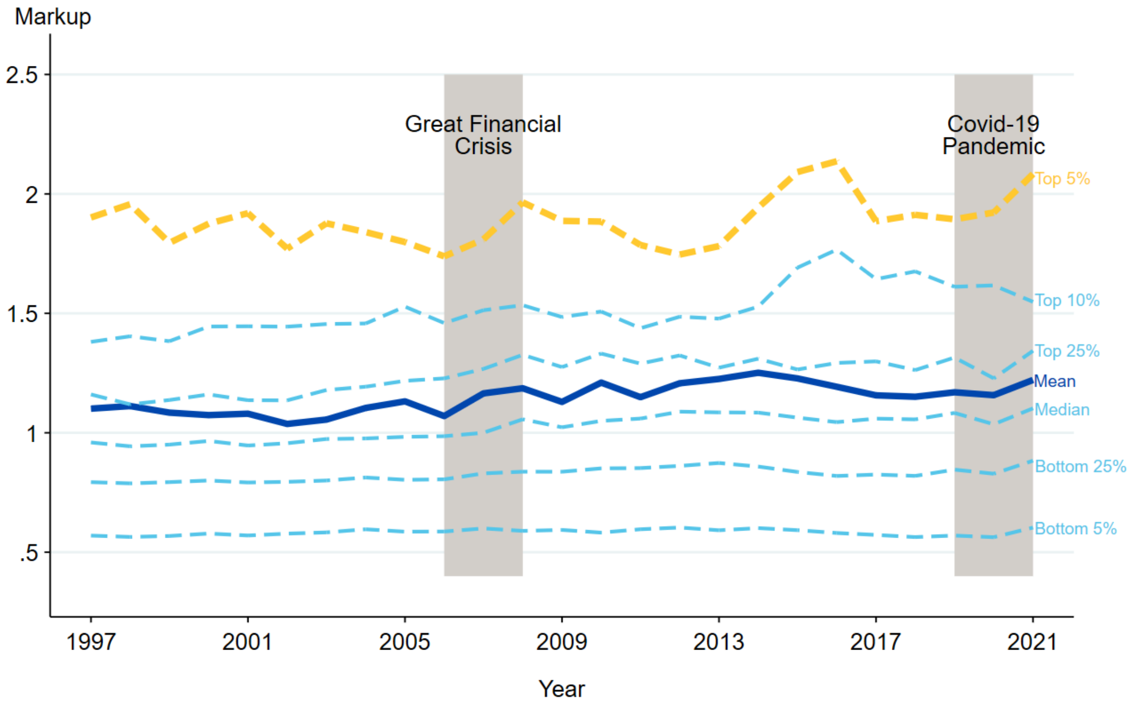
2.38 Markups at high-markup and low-markup firms have evolved very differently over the past twenty-five years. Markups in the bottom quartile have hardly increased at all. Markups in the middle of the distribution have increased somewhat, in line with the moderate rise in average markups. Markups have risen more (three times as much by some measures) at the top of the markup distribution than they have elsewhere.

2.39 Black (2022) and Aquilante, Chowla, Dacic, Haldane, Masolo, Schneider, Seneca and Tatomir (2019) establish a similar picture at the industry level. Within industries, the biggest rise in markups has happened at the top of the distribution while for the median firm, markups have remained constant.

2.40 Not all firms contribute equally to the overall rise in markups. This is important because characteristics of high-markup firms can give us clues as to why markups have increased over time, and therefore how policymakers might choose to react to this change.

Figure 10: Markups have risen more at the top of the distribution than elsewhere

Evolution of average markups in different quantiles of the markup distribution. Data from Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey (ABS) 2021. GB only



Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Selected quantiles of the markup distribution. Data from the *Annual Respondents Databes X* (1997-2020) and *Annual Business Survey* (2021).

2.41 We first show how key firm characteristics like age, size, profit shares and labour shares are related to markups across the economy. The profit share measures what fraction of a firm's sales are retained as profits, and the labour share measures the fraction of sales that are used to meet employment costs.

2.42 As markups represent the profit on each additional sale, we expect markups to be positively correlated with the profit share. The closeness of this relationship depends on fixed costs and the returns to scale of the production technology. For instance, if firms incur large fixed costs such as marketing overheads, they might have large markups but a small profit share.

2.43 As for the labour share, recent work suggests higher concentration in output markets is associated with lower labour shares (e.g., Autor, Dorn, Katz, Patterson, Van Reenen, 2020; De Loecker, Eeckhout and Unger, 2020; Deb, Eeckhout, Patel and Warren, 2023). Higher markups require firms to produce less than in a competitive market, so they hire less labour. Therefore, absent offsetting technological changes, higher markups will be associated with a lower labour share, all else equal.

2.44 However, these average relationships may be misleading if we look at them in isolation: firms that are bigger may also be older, less labour-intensive, or concentrated in different industries. Therefore, we also report residual relationships between these key characteristics after comparing firms that otherwise look similar to each other.

2.45 Figure 11 shows in four panels the overall relationship between markups and age, size, profit shares and labour shares respectively, averaged over the whole period. High-markup firms are generally younger, bigger, and more profitable. The labour share shows a U-shaped relationship with markups: the firms with the lowest and highest labour share have much higher markups than firms with intermediate labour shares.

Figure 11: Before controlling for firm characteristics, firms with high markups are on average younger, bigger and more profitable

Average and confidence interval of firm-level markups across bins of firm age, employment, profit share and labour share. Data from Annual Respondents Database X (ARDx) 1992-2020 and Annual Business Survey (ABS) 2021. GB only

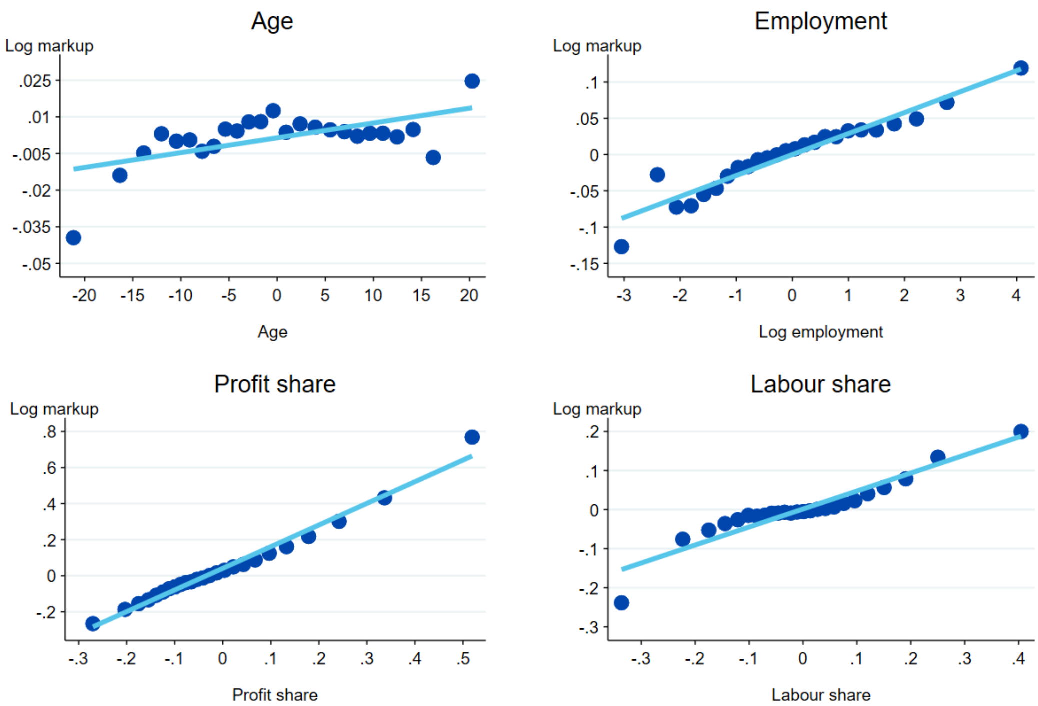
Average and confidence interval of firm-level markups across bins of firm age, employment, profit share and labour share. Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1992-2020) and the *Annual Business Database* (2021).

2.46 Many of these relationships hold even within industry and year, as shown in Figure 12. In particular, the relationship between markups and size and profit margins is still positive. As we might expect, larger and more profitable firms have higher markups.

2.47 However, once we control for other firm characteristics, the relationship between markups and age and the labour share, respectively, also become positive. In other words, in Great Britain older firms and firms with a higher labour share have higher markups. This correlation may reflect rent-sharing between employers and employees or could be a reflection of how firms with higher markups employ different types of workers.

Figure 12: After controlling for firm characteristics, firms with high markups are on average older, bigger, more profitable and have a higher labour share

Binned scatterplot of residuals from regressions of log markups on age, log employment, profit share, labour share, after controlling for year and industry. Data from Annual Respondents Database X (ARDx) 1992-2020 and Annual Business Survey (ABS) 2021. GB only



Binned scatterplot residuals from regressions of log markups on age, log employment, profit share and labour share after controlling for year and industry. Markups are estimated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1992-2020) and the *Annual Business Survey* 2021

2.48 In addition, existing academic research (Gutiérrez and Philippon, 2017) has found that markups are also related to the financial choices firms make.

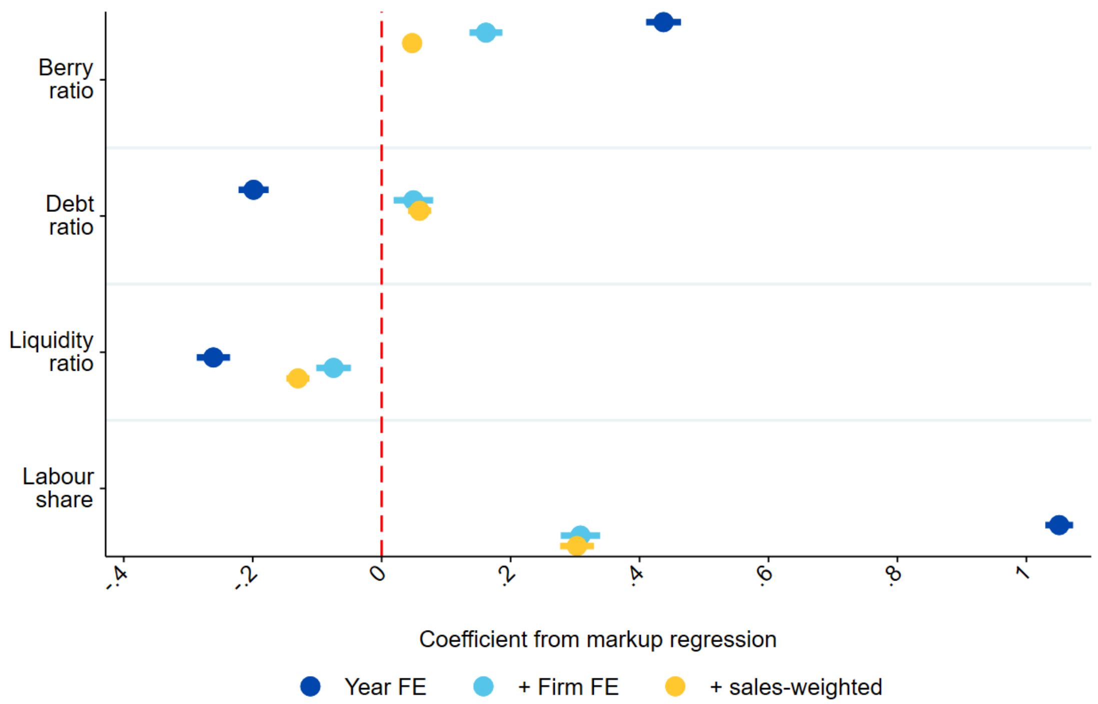
However, our primary data source does not contain balance sheet information that would allow us to replicate this analysis.

2.49 We have therefore conducted supplementary analysis using Bureau van Dijk's FAME dataset and the methodology that we used in the CMA's previous State of Competition report (2022).

2.50 While our baseline methodological approach is more robust, Figure E.1 in the appendix shows that overall markup trends using this alternative data source and methodology are similar to our preferred baseline. Figure 13 below also shows that the relationship between markups and the labour share (which we can also calculate using FAME data) is comparable to what we find in our baseline data.

Figure 13: Markups are consistently positively related to profits, overall debt, and the labour share, and negatively related to short-term liquidity

Regression coefficients of markups on Berry ratio, debt ratio, liquidity ratio and labour share under different model specifications. Controls include year fixed effects, firm fixed effects, and observations weighted by turnover. Data from Bureau van Dijk's FAME 2013-2023. UK



Coefficients from various regression specifications of markups on financial variables. Markup estimated using cost share method, with fixed assets. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Berry ratio = gross profit/operating expenses. Debt ratio = total liabilities/total assets. Liquidity ratio = current assets/current liabilities. Labour share = total remuneration/turnover. Data from *Bureau van Dijk's FAME* (2013-2023).

2.51 This gives us some confidence that despite the differences in the business population included, information collected, and methodologies used, we obtain results that are informative of the overall relationships in the UK economy.

2.52 We examine three financial characteristics of firms. First, we look at the Berry ratio, which compares gross profits to operating expenses. This is an alternative measure of the profit firms make, and therefore the extent of their market power. Second, we examine the debt ratio, which measures the amount of debt they have taken on as a percentage of their total assets. Finally, we investigate the liquidity ratio, which measures how comfortably companies can repay short-term debts, and therefore how cash-constrained they are.

2.53 Figure 13 shows the relationship between markups and each of these variables in the form of regression coefficients. To compare firms that are more like for like, we use fixed effects to remove year- and firm-specific confounders. In other words, we look at how changes in these variables are related to changes in markups over time for the same firm, after flexibly accounting for common time trends. We also normalise the variables so that coefficient magnitudes are comparable across the different regressions.

2.54 We find that markups are positively related to the Berry ratio. This makes sense since this is a measure of profits, and therefore market power. As in our baseline data, markups are also positively related to the labour share. Finally, markups are positively related to a firm's debt ratio, a measure of its leverage, but negatively related to the liquidity ratio, a measure of its cash flow position.

2.55 Existing research also finds that firms' financial and strategic choices are systematically related to their markups. De Loecker, Obermeier and Van Reenen (2022) find that the markup rise is stronger in listed firms, which tend to be larger and more global than unlisted firms. Aquilante, Chowla, Dacic, Haldane, Masolo, Schneider, Seneca and Tatomir (2019) find that firms that sell their goods internationally are the driving force behind the observed increase in markups.

2.56 This chapter has shown that markups in Great Britain have increased on average by 10% since 1997. Most of this change is driven by services and within-sector changes rather than reallocation. Markups have risen more at the top than at the middle or lower end of the markup distribution. High-markup firms tend to be bigger, older, more profitable, and different in their use of labour and financing.

2.57 The next chapters explore to what extent this change in average markups may be explained by changes in market structure, the dynamism of the economy, technological changes and merger and acquisition activity.

3 Market power and market structure

3.1 Market power is the outcome of the competitive behaviour of firms in the markets they operate in. This behaviour in turn is shaped by the structure of these markets: their geographical span, exposure to international competition, the structure of supply linkages, and the relationships between the ultimate owners of each firm.

3.2 In this chapter, we therefore look at how UK markets have changed on average on all these dimensions. This will help us better understand the observed rise in the average markups.

3.3 We find that UK market concentration has not increased over time, despite the rise in markups. Additionally, we find that exposure to international trade is negatively related to markups, suggesting that international competition also constrains domestic market power.

3.4 Firms do not only have market power in output markets but may also have market power in input markets. Drawing on recent CMA work, we show that input market power in GB labour markets has declined in recent decades. Finally, we find evidence of ownership linkages within and between industries which may affect how firms compete.

Measuring market structure

3.5 In the past, economists have often looked at the number of firms in a market as a proxy for the strength of competition. This approach has come under scrutiny, as technologies, market size and other factors also determine concentration.

3.6 The presence of similar products or the threat of entrants may also constrain market power in a market, even when the number of incumbent firms is low.

3.7 As a result, concentration is perhaps a less useful measure of market power than cost markups. Nonetheless, it tells us something about how markets function, and how they have changed over time.

3.8 A common measure of concentration is the share of an industry's turnover accounted for by the largest firms. We can compute this by summing the market shares of the n largest firms (the so-called concentration ratio, or CR_n). Commonly used concentration ratios are the CR5 which measures the total market share of the five largest firms, or the CR10, which measures the share of the ten largest firms.

3.9 Alternatively, we can sum the market shares of all firms in the market. To give larger firms a larger weight, we square the market shares first. The resulting measure is called the Herfindahl-Hirschman Index (or HHI for short). It ranges from zero for a perfectly competitive market to 10,000 for a monopoly.

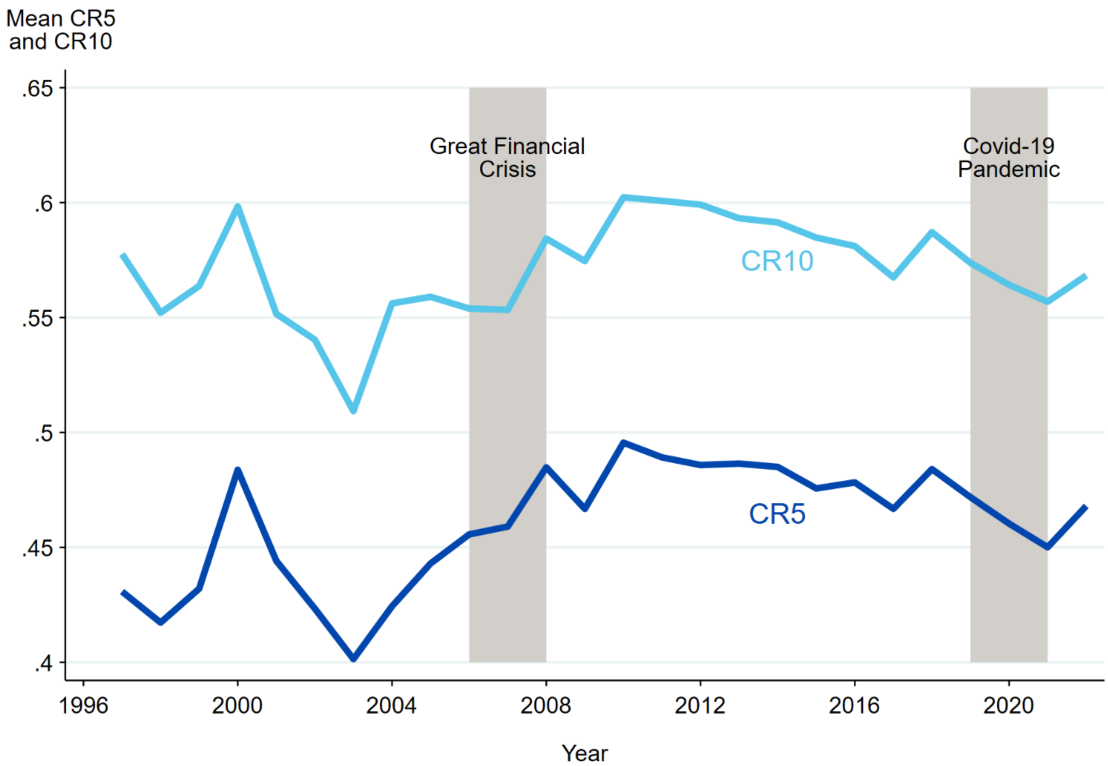
3.10 Competition agencies sometimes define markets with an HHI of above 1,500 as moderately concentrated, and those with an HHI of above 2,500 as highly concentrated.

Concentration has remained relatively stable on average

3.11 Figure 14 plots the average concentration ratio for the five and ten largest firms in each four-digit Standard Industrial Classification (SIC) industry between 1997 and 2022.

Figure 14: Mean CR5 and CR10 have remained roughly stable after the Great Financial Crisis

Mean concentration ratios (CR5 and CR10) computed at the four-digit Standard Industial Classification (SIC) level and aggregated by weighting for industry turnover. Data from Business Structure Database (BSD) 1997 – 2022. UK



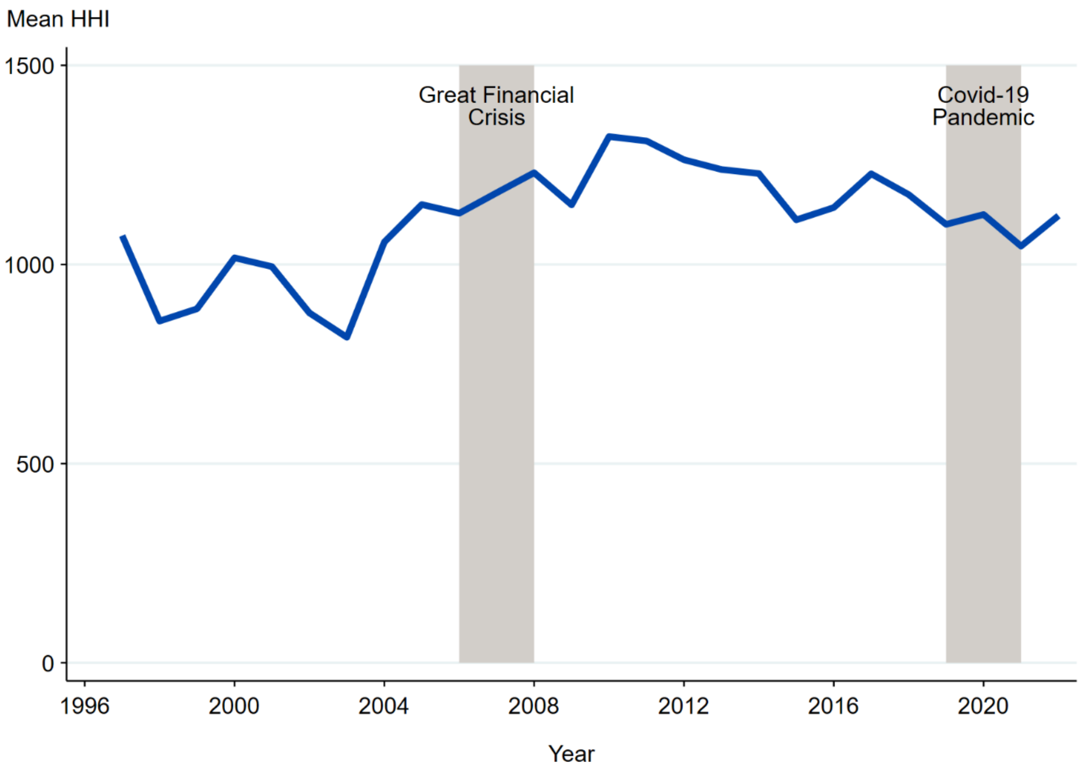
CR5 and CR10 calculated at 4-digit Standard Industrial Classification (SIC) level for each year. Weighted mean using industry turnover as weight. All SIC sectors included. Data from the *Business Structure Database* (1997-2022)

3.12 The overall change in average concentration ratios over the past twenty-five years has been small. The ratios declined sharply in the early 2000s then peaked around 2010. Both the CR5 and the CR10 have stabilised in more recent years. Overall, there has been no increase in the CR10 since 1997, while the CR5 has risen from around 43% to 47%, signalling a small average increase in the market shares of the very top players in each industry.

3.13 Figure 15 shows the development of the whole-economy HHI over the same period. The average HHI has experienced a similar dynamic as the concentration ratios, with most of the changes happening from the early 2000s to 2010. Overall, the average HHI has increased from slightly less than 1,100 in 1997 to 1,300, before falling back down to just above 1,100 in 2022.

Figure 15: The average HHI has remained roughly stable after the Great Financial Crisis

Mean Herfindahl-Hirschman Index (HHI) is a turnover-weighted aggregation of the HHIs at the four-digit Standard Industrial Classification (SIC) level. Data from Business Structure Database (BSD) 1997 – 2022. UK



Herfindahl Hirschman Index calculated at 4-digit Standard Industrial Classification (SIC) level for each year. Weighted mean using industry turnover as weight. All SIC sectors included. Data from the *Business Structure Database* (1997-2022).

3.14 By the usual standards competition agencies use, average concentration levels are therefore stable and moderate. However, we expect most markets to be smaller than four-digit SIC industries, and market-level HHIs therefore to be higher. The typical industry (even for small industries) spans multiple products or services, each typically a market of its own. Additionally, some markets are local and national industry measures therefore define markets that are again too broad.

3.15 The economy-wide average can mask differences in sectoral dynamics, as Figure 16 and Figure 17 show. Arts and entertainment (responsible for a relatively small share of the economy, at 1.2% of overall turnover in 2022) is the only sector to have seen a substantial rise in concentration by all measures. Most of this rise has taken place prior to the Great Financial Crisis. Concentration has also increased slightly in wholesale and retail, manufacturing, construction, and other services. Other sectors have seen smaller increases or decreases, according to which measure is used.

3.16 Academic research finds similar trends to this report. Aquilante, Chowla, Dacic, Haldane, Masolo, Schneider, Seneca and Tatomir (2019) estimate that the CR100 concentration ratio (the market share of the one hundred largest firms across large sectors) has increased from 20% in 1998 to 28% in 2016, with the trend flattening out since the Great Financial Crisis. Bell and Tomlinson (2018) find the same pattern but obtain a slightly lower estimate of 18.5% in 2003 and 23% in 2016.

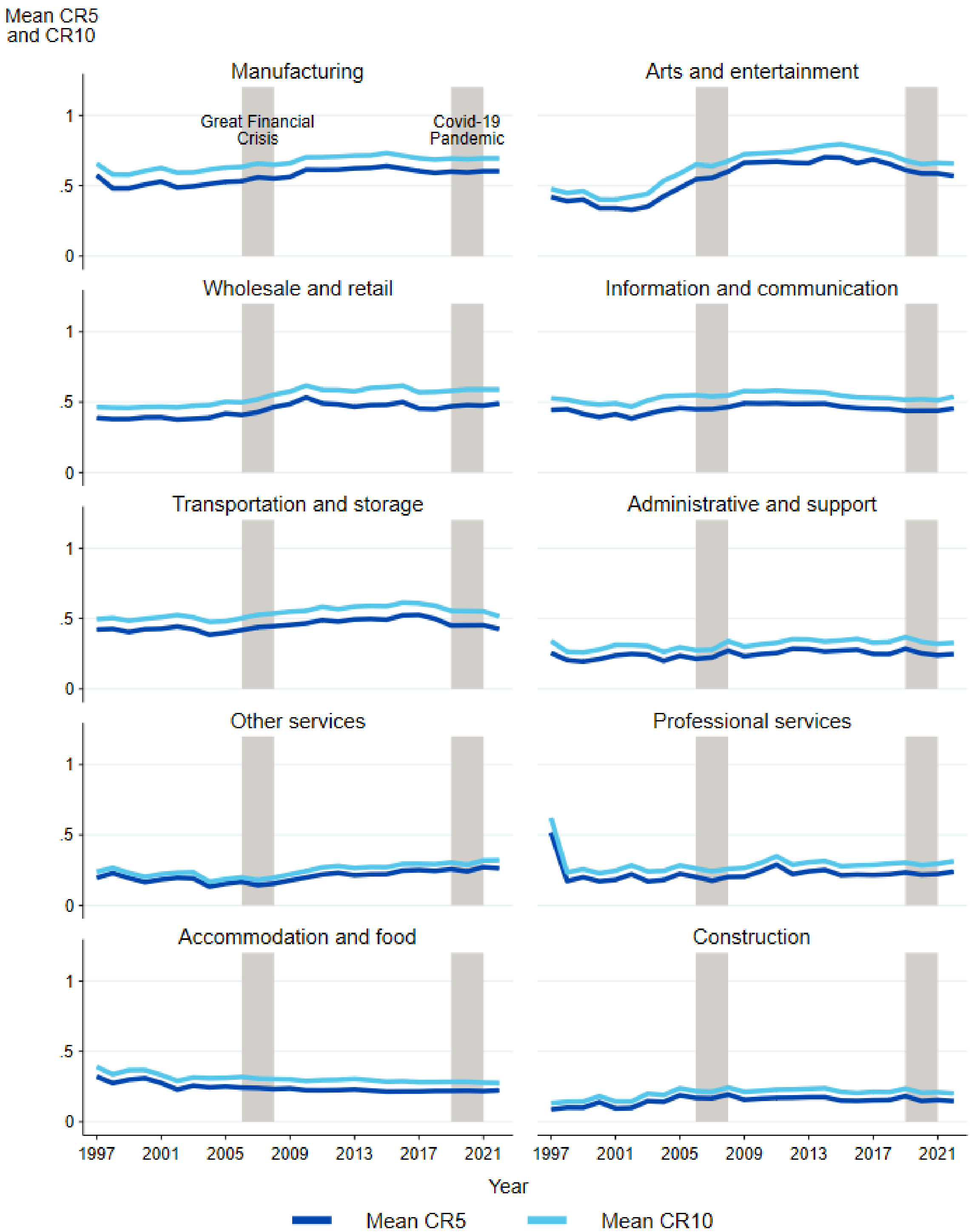
3.17 Kim and Savagar (2023) find that aggregate measures of concentration in the UK are stable or even very slightly decreasing between 1997 and 2018. The aggregate CR5, CR10 and CR20 fluctuate around a constant value from 2008 onwards.

3.18 The picture in the US is markedly different. Autor, Dorn, Katz, Patterson and Van Reenen (2017) find a clear rise in CR4 and CR20 concentration within six major sectors of the US economy between 1995 and 2012. The increase in the CR4 index is over 40% in services, finance, and retail between 2000 and 2014. This increase in concentration does not seem to be driven by digital-intensive sectors.

3.19 The European evidence is more mixed. Bighelli, di Mauro, Melitz and Mertens (2023) examine data from 15 European countries from 2009 to 2016 and document an increase of 43% in aggregate concentration. Concentration is primarily rising due to the reallocation of economic activity towards large and more concentrated industries, mostly located in Germany. Bajgar, Berlingieri, Calligaris, Criscuolo and Timmis (2023) find that CR4 concentration in the mean European two-digit sector has increased by 20% between 2000 and 2014. As in the US, the increase in concentration does not seem to be driven by digital-intensive sectors.

Figure 16: At a sectoral level, the change in concentration ratios is heterogeneous, with arts and entertainment experiencing the strongest increase

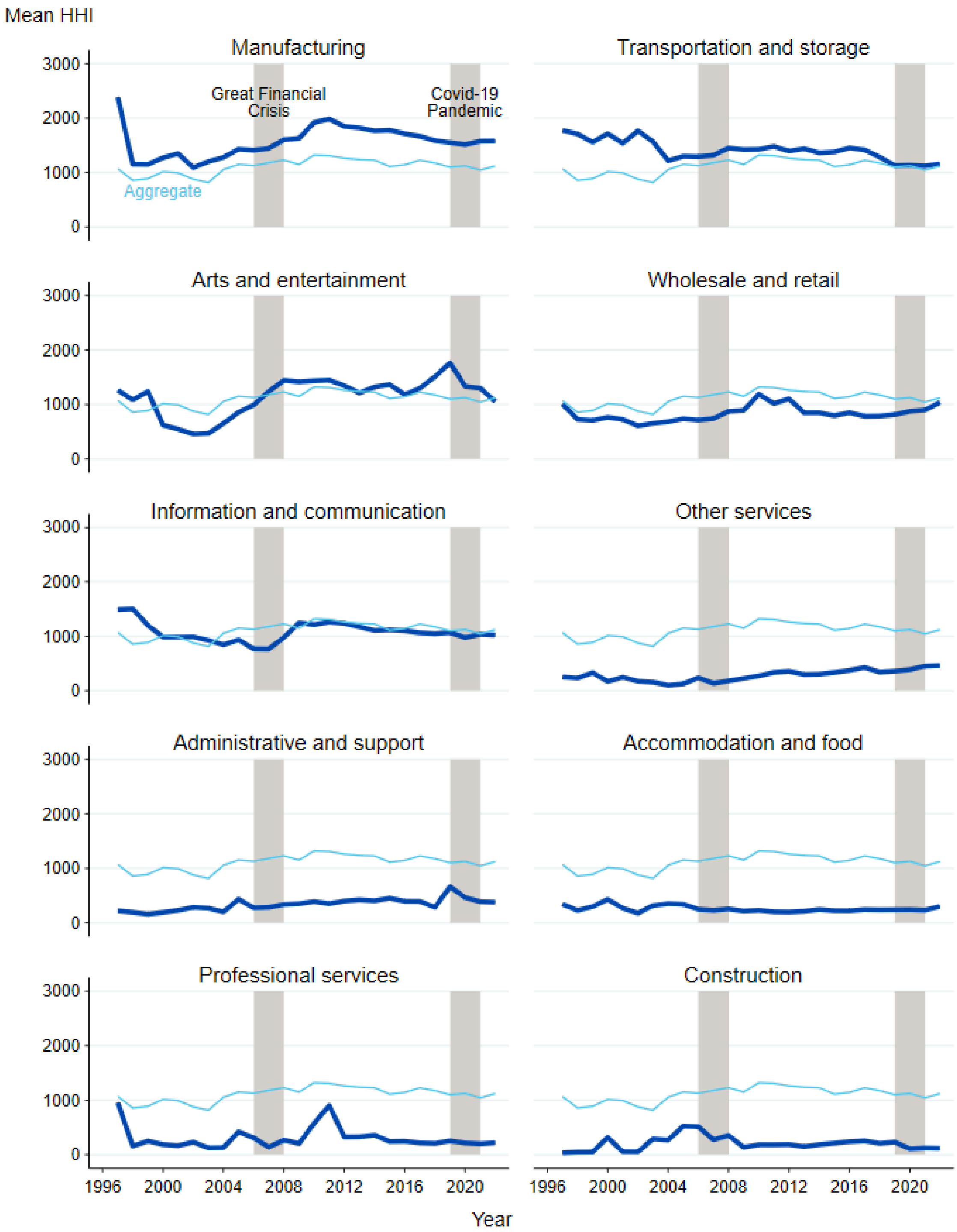
Mean sectoral CR5 and CR10 computed as turnover-weighted aggregation of ratios at the four-digit Standard Industrial Classification (SIC) level. Data from Business Structure Database (BSD) 1997 – 2022. UK



CR5 and CR10 calculated at 4-digit Standard Industrial Classification (SIC) level for each year. Weighted mean using industry turnover as weight. Industries are ranked by highest CR10 in 2022. Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Data from the *Business Structure Database* (1997-2022).

Figure 17: Sectoral average HHIs vary but are mostly stable

Mean sectoral Herfindahl-Hirschman Index (HHI) computed as turnover-weighted aggregation of HHIs at the four-digit Standard Industrial Classification (SIC) level. Data from Business Structure Database (BSD) 1997 – 2022. UK



HHI calculated at 4-digit Standard Industrial Classification (SIC) level for each year. Weighted mean using industry turnover as weight. Industries are ranked by highest HHI in 2022. Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Data from the *Business Structure Database* (1997-2022).

3.20 Two studies however find stable concentration levels. Cavalleri, Eliet, McAdam, Petroulakis, Soares and Vansteenkiste (2019) document flat concentration trends in Germany, France, Spain, and Italy since 2006. Similarly, Gutiérrez and Philippon (2018) report flat concentration trends at the European level since 2000.

3.21 Concentration measures are one way to try to understand what has driven the changes in markups. But these measures only capture one aspect of how markets are organised: the extent to which domestic production of goods and services are concentrated in the hands of a few firms.

3.22 This leaves out other elements of market structure needed to understand market power in the UK, like competition from foreign-based firms, market power in input markets, vertical relationships between firms and the ultimate ownership links across the economy. The rest of this chapter examines each of these in turn.

International trade acts as a constraint on market power

3.23 Where foreign-based firms have access to UK markets, they can constrain the market power of UK firms. Therefore, concentration measures of domestic producers may present a misleading picture.

3.24 Figure 18 shows the relationship between average imports as a fraction of turnover (a measure of trade openness, and therefore a proxy of the level of international competition faced by an industry) and average markups at the two-digit SIC level between 2016 and 2021.

3.25 Since final output estimates of imports are reported at the product but not the industry level and mapping products to industries is not straightforward, we use an industry-level measure of imports that includes both goods for sale and inputs used by firms in the production process.

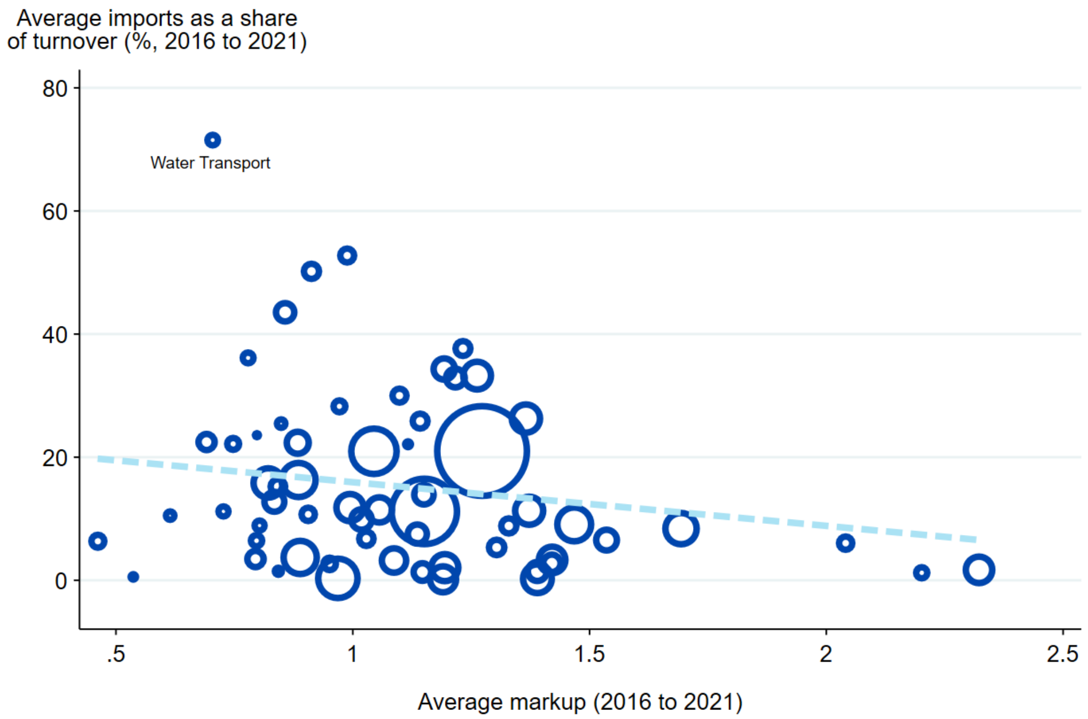
3.26 Despite the statistical noise introduced by the imperfect measure of imports, industries that face greater competition from abroad have less market power. This is true regardless of the precise definition of trade openness, as additional Figures E.4 to E.7 in the appendix show.

3.27 International trade not only means that foreign firms can compete in UK markets, but also that domestic firms can compete abroad. Market access abroad creates an opportunity for domestic firms to increase their profits, either by increasing their markups or by selling to a larger market.

3.28 Of course, firms make active and often costly choices to become exporters. Those that do are often very different from the average firm in the economy. If we want to understand the impact of exporting on a firm's markup, we cannot therefore simply compare the markups of firms that export to those that do not. Instead, we look at changes in markups when a firm's export status changes over time and include additional controls to compare firms that are similar to each other. This allows us to compare markups within a firm when the same firm starts exporting.

Figure 18: Higher exposure to imports is negatively correlated with markups

Scatterplot of the average expenditure on imports relative to turnover against average markups at the two-digit Standard Industrial Classification level between 2016 and 2021, from Annual Respondent Database x (1997-2020), Annual Business Survey (2021), Business Structure Database (1997-2022) and ONS UK Trade in services/goods by industry, country, and service type (2016-2021)



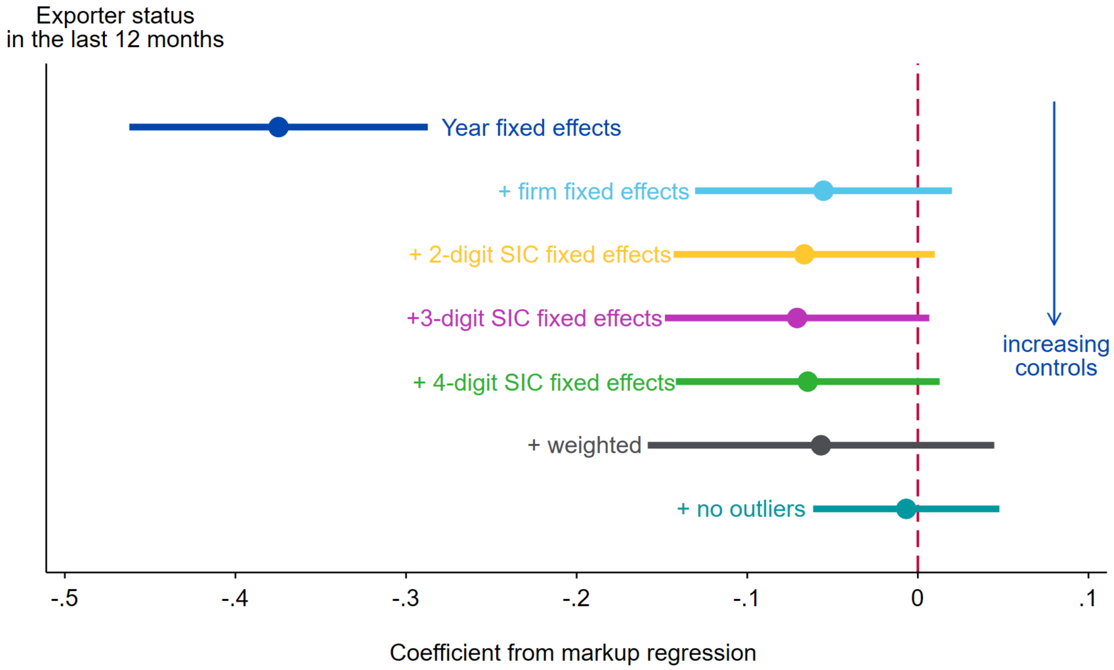
Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fit weighted by turnover, not statistically significant at the 5% level (as represented by the dashed line). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and 2-digit sectors that we do not have data for in every single year. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), *ONS UK trade in services/ goods by industry, country and service type, imports* (2016-2021) and the *Business Structure Database*(1997-2022).

3.29 When we look at the relationship between exporting and markups within the same firm, we do not find that exporting is associated with higher markups. Figure 19 plots the coefficients from this regression of markups on export status and other controls. The central dots represent regression coefficients from regressions of markups on export status, and the horizontal bars represent the plausible range of alternative estimates. Each row includes more controls than the previous one, to make the comparison as like-for-like as possible.

3.30 Once we look at the relationship between export status and markups for the same firm over time (that is, in the second row), we do not find that exporting is associated with higher or lower markups. This does not mean exporting does not confer other advantages. For instance, by selling to more buyers, firms gain the ability to make their markup over a larger number of sales and therefore potentially achieve larger overall profits.

Figure 19: Firms that export do not necessarily have markups different from similar, domestic-only firms

Regression coefficients of markups on exporter status of the firm in the last 12 months. Different specifications include year fixed effects, firm fixed effects, various industry fixed effects, observations weighted by turnover and outlier removal. Data from the Annual Respondents Database X (1997-2020) and Annual Business Survey (2021). GB only



Coefficients from various regression specifications of markups on exporter status of the firm in the last 12 months. Markups are estimated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L,O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021).

Market power and the structure of the economy

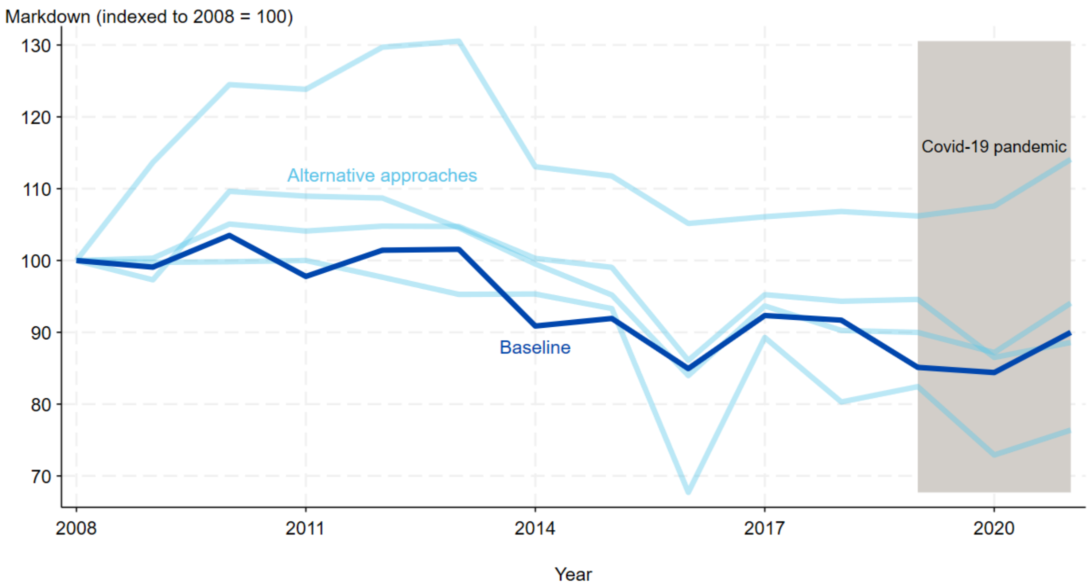
3.31 Beyond exposure to international trade, many other aspects of individual markets matter for our assessment of the extent of market power across the UK economy. Many of them are hard to measure and understand across the whole economy. This section gives an initial glimpse into three of these: market power in input markets, market power along supply chains, and ownership links across companies.

3.32 Firms' market power often extends beyond just product markets. As recent work by the CMA (2024) shows, most firms have some market power in labour markets too.

3.33 However, Figure 20 shows that average wage markdowns, the most direct measure of labour market power, have fallen slightly in Great Britain in the past decade, which indicates that in labour markets, power has shifted away from employers and towards employees. This contrasts with evidence from the US, where labour market power appears to have risen.

Figure 20: Employer market power measured via wage markdowns is constant or declining

Whole-economy mean markdown series from a variety of production function estimation approaches (100 = 2008 values), from the Annual Business Survey, 2008-2021. GB only



Markdown estimated following baseline production function approach in this report. Data from the *Annual Respondents Database X* (1997 - 2020) and *Annual Business Survey* (2021). Alternative methods are different production functions, with/without control function approaches. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, P, Q, T, U.

3.34 When firms have market power in both input and output markets, output and prices are further distorted. This can be true even for inputs that are themselves traded in markets where there is no market power. For instance, labour market power may distort choices in material input markets.

3.35 This holds true not just for labour markets, but for any input. Many firms do not directly supply consumers, but instead supply other firms. There may be many such business-to-business transactions before the final product reaches consumers.

3.36 This may have important implications for market power in the overall economy. First, business-to-business transactions may be less visible to the public eye and may therefore escape the attention of competition authorities. Second, if several firms along a supply chain have market power, the outcome will be worse than having a single monopolist, because no firm considers the additional distortion it imposes on other firms along the supply chain.

3.37 Following existing academic studies (Antràs, Chor, Fally and Hillberry, 2012; Fally, 2012; Antràs and Chor, 2022), we compute a simple measure of "upstreamness" by inverting the UK's input-output tables and use it to look at market power along supply chains.

3.38 Input-output tables measure what fraction of an industry's output becomes an input for which other industries. By tracing these links through the entire table, we can obtain a measure of how far upstream from end consumers on average an industry sits in supply chains.

3.39 Figure 21 shows that on average, industries located further upstream in supply chains have higher markups. For instance, employment services (the two-digit industry with the highest markup) is on average four links in the supply chain removed from the final consumer. However, the relationship between upstreamness and markups is noisy and not statistically significant, and further research into it would be helpful.

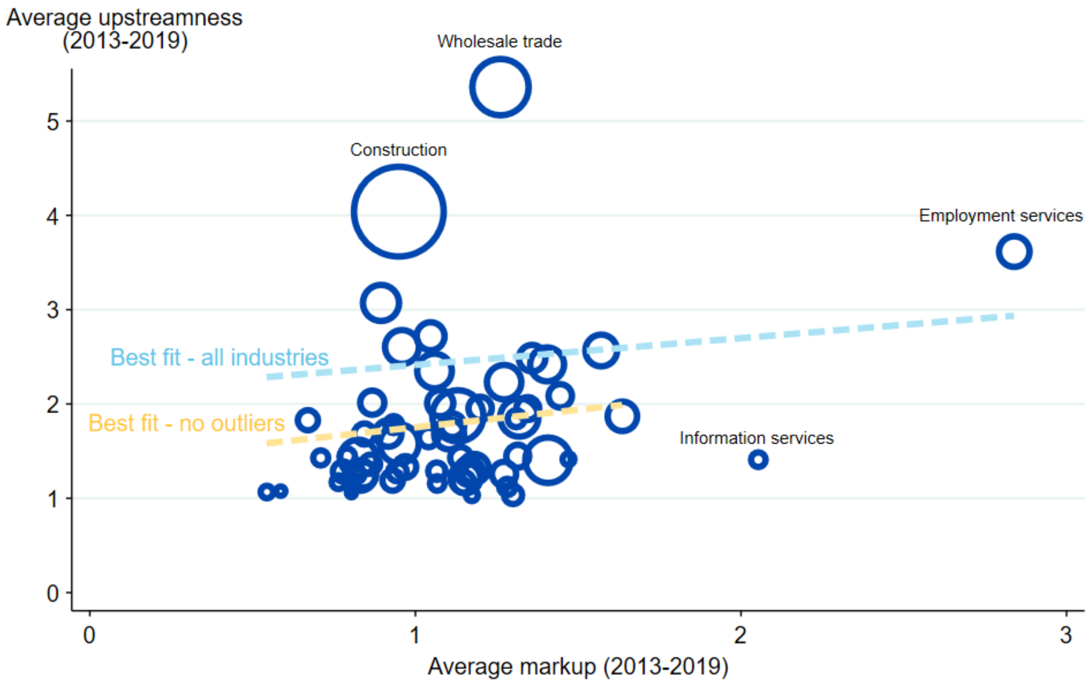
3.40 Finally, just as it is important to understand real economic links between different industries to fully understand market power, it is also important to understand financial links between firms.

3.41 In recent years, evidence has accumulated that firms in the same industry that share ultimate owners may lack incentives to compete vigorously. Ultimately, these common owners benefit from lax competition and may therefore fail to push managers to compete aggressively (Azar, Schmalz and Tecu, 2018; Antón, Ederer, Giné, Schmalz, 2022).

3.42 But the degree of ownership linkages may matter for other reasons too. The supply chain links that firms form may be influenced by their ownership links. Commonly owned firms may also share resources or hedge risks (Cestone, Fumagalli, Kramarz, Pica, 2023; Boutin, Cestone, Fumagalli, Pica and Serrano-Velardek, 2013; He and Huang, 2017).

Figure 21: Industries close to consumers generally have low markups

Scatterplot of average distance from final consumers (upstreamness) against average markup level. Each bubble represents a two-digit industry (or collection of) and its size denotes the average sectoral share. Data from the Annual Respondents Database X (1997-2020), Annual Business Survey (2021) and input-output tables (2013-2019). GB only



Each data point represents a single (or collection of) 2-digit Standard Industrial Classification (SIC) sector averaged over the period 2013 to 2019, size represents average sectoral share. Linear fits weighted by sectoral share, not statistically significant at the 5% level (as represented by the dashed lines). Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997 - 2020) and *Annual Business Survey* (2021). Upstreamness measures the number of production stages from final use. Data from *input-output tables* (2013 - 2019).

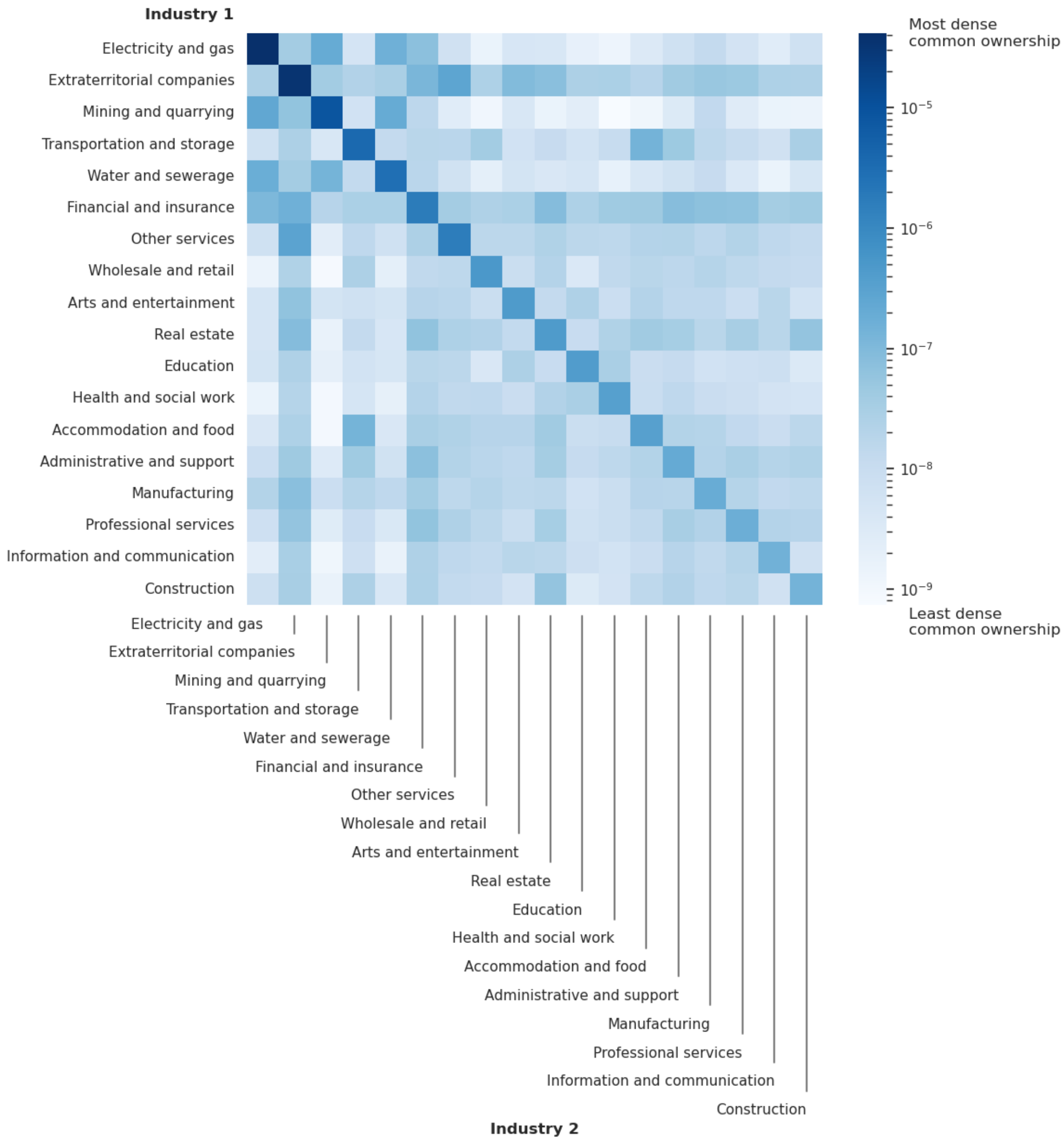
3.43 Recent academic research has also suggested that common ownership and the identity of owners can influence the incentives for firms to compete (Ederer and Pellegrino, 2024). Therefore, ownership linkages may be important for consumer outcomes.

3.44 Figure 22, which comes from a forthcoming CMA report on ownership networks in the UK, plots the density of common and cross-ownership for incorporated UK businesses. The darker blue squares indicate industries which have more overlapping ownership. The diagonal squares show within-industry ownership links, and the off-diagonal squares show cross-industry links.

3.45 Figure 22 shows that within-industry common ownership is much more likely than cross-industry common ownership. From a competition perspective, within-industry common ownership is likely to raise more concerns than cross-industry common ownership, because common ownership of firms in the same industry may reduce their incentives to compete vigorously with one another.

Figure 22: Ownership networks are more common within broad industries than across, consistent with anti-competitive theories of common ownership

Heatmap describing the (network) density of common ownership links between Standard Industrial Classification (SIC) sections. Dark blue squares indicate dense common ownership. Data from Companies House, UK 2024



Each square gives the (network) density between industries for the network of companies linked by common ownership, restricted to the two industries in the axes.
Data from a 2024 snapshot of all companies registered with Companies House. UK.

3.46 If on the other hand common ownership is due to a desire to diversify risk, we would expect to see more cross-industry common ownership. In the chart, this would correspond to darker off-diagonal squares than squares on the diagonal. For cross-industry ownership, finance and extraterritorial companies play an important role in linking many different industries. This may indicate an important coordinating role for these industries.

3.47 Ongoing CMA work, which we expect to publish in the coming months, explores the characteristics of ownership networks and the firms that form them in more detail, for instance by zooming in on much more granular industries, and linking cross- and common ownership to industry structure and outcomes.

The structure of the economy matters for competition

3.48 In sum, despite the rise in markups, static measures of market concentration have been relatively stable in the last ten years. This is true both at the top when we look at the share of the largest firms, and for whole industries in the form of their HHI.

3.49 But domestic concentration in horizontal industries only paints a very partial picture. We show that international trade openness is correlated with lower markups, indicating that competition from abroad may constrain market power.

3.50 While current methods focus on market power in output markets, recent CMA work shows that input markets like labour markets may also be affected by market power. Finally, this section demonstrates the need for more evidence on how industries are connected to each other: markups appear slightly higher further up supply chains, and ownership linkages both within and across industries are significant.

4 Market power and business dynamism

4.1 The previous chapters have focused on static measures of competition at a given point in time. How much are firms charging above their marginal cost? What share of the market is held by the largest firms in an industry each year?

4.2 The number of firms in a market is one possible indicator of competition in a market. But the prevailing technology in an industry also matters for concentration, and, in any case, it only provides a static view of how firms interact.

4.3 A different view of markets emphasises the dynamic aspects of competition: the ability of new entrants to displace incumbents, the introduction of new ideas into the economy by way of entry and exit of firms, and the constant churn of labour and capital as firms try to find their most productive use.

4.4 Collectively, this economic churn is sometimes referred to as “business dynamism” and often associated with the work of Austrian economist Joseph Schumpeter. Schumpeter coined the term “creative destruction” to describe the replacement of existing products, processes, and ideas by new entrants eager to capture a market.

4.5 We find that across different measures, the dynamism of the UK economy has fallen slightly over the past twenty-five years. Firm entry and exit rates have fallen across most sectors, and the job reallocation rate has declined. At the top of most industries, the largest firms are more likely to keep their position over multiple years. Young firms account for a smaller share of turnover and employment than they did twenty years ago.

4.6 This may indicate a slowdown in the rate with which new ideas, products, and processes, which are crucial for economic growth, enter the UK economy and spread between firms.

Dynamic measures of competition

4.7 In a healthy economy, more productive firms constantly replace less productive ones in a continuous process of reallocation of economic activity: this is often called “business dynamism”.

4.8 In this report, we measure business dynamism in four ways. First, we compute entry and exit rates of firms, at the aggregate and sector levels.

4.9 Second, we measure what share of employment in an industry changes hands from one year to the next: this is called the job reallocation rate. The job reallocation rate considers both job creation and job destruction, coming from both incumbent firms and those that enter or exit.

4.10 Third, we measure the persistence over time of the largest firms by turnover at the top of an industry. If the same firms are at the top year after year, this indicates a lack of dynamism.

4.11 Finally, we compute the share of turnover and employment accounted for by young firms (those created within the last five years). This is another measure of how successful new entrants are in displacing incumbent firms.

4.12 The analysis in this chapter suggests a slowdown of business dynamism in the UK by any of these measures. Entry and exit rates, the job reallocation rate and the employment and turnover shares of young firms have all fallen over time. Persistence of the same firms at the top of each industry has increased. These trends hold in most sectors, with only a few exceptions.

Firm entry and exit rates have declined

4.13 Economy-wide entry and exit rates have trended downwards between 2005 and 2016 and stabilised at their new, lower level until Covid-19, as shown in Figure 23. While historically close to each other, from 2012 until 2021 entry rates exceeded exit rates. This means that the active business population has expanded, prompting discussions about so-called “zombie firms” (firms that are not economically viable but survive, tying up resources).

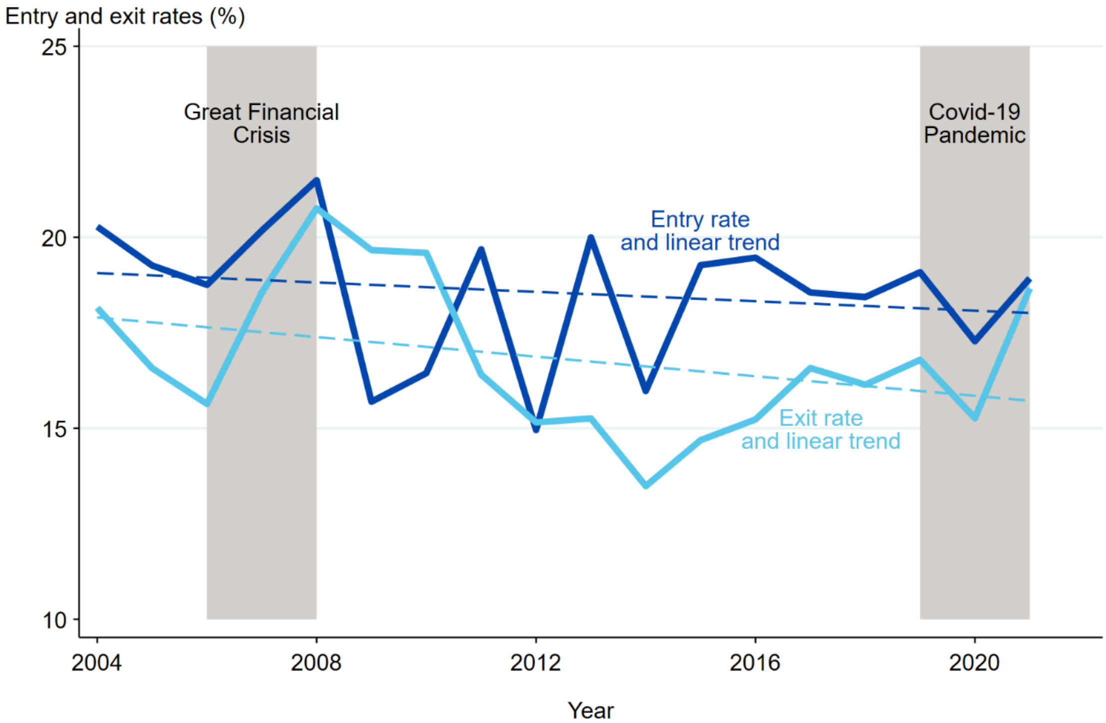
4.14 While there is a clear and large impact of the Great Financial Crisis, the entry and exit rates have changed less during Covid-19. During the pandemic, both entry and exit rates initially fell sharply, but the exit rate has risen faster in 2021 reaching almost the same level as the entry rate. The fast rise in exit rates may lessen concerns about the persistence of zombie firms.

4.15 While in the last year the entry rate has risen slightly, we have yet to see the post-pandemic explosion of entrepreneurial activity seen in the US in recent years (Decker and Haltiwanger, 2023).

4.16 Across sectors, the decline in entry and exit rates is broadly similar, as Figure 24 shows. Two exceptions are transportation and storage and wholesale and retail. Both sectors have seen rising entry and exit rates since the mid-2010s.

Figure 23: Annual entry and exit rates have fallen slightly since 2004

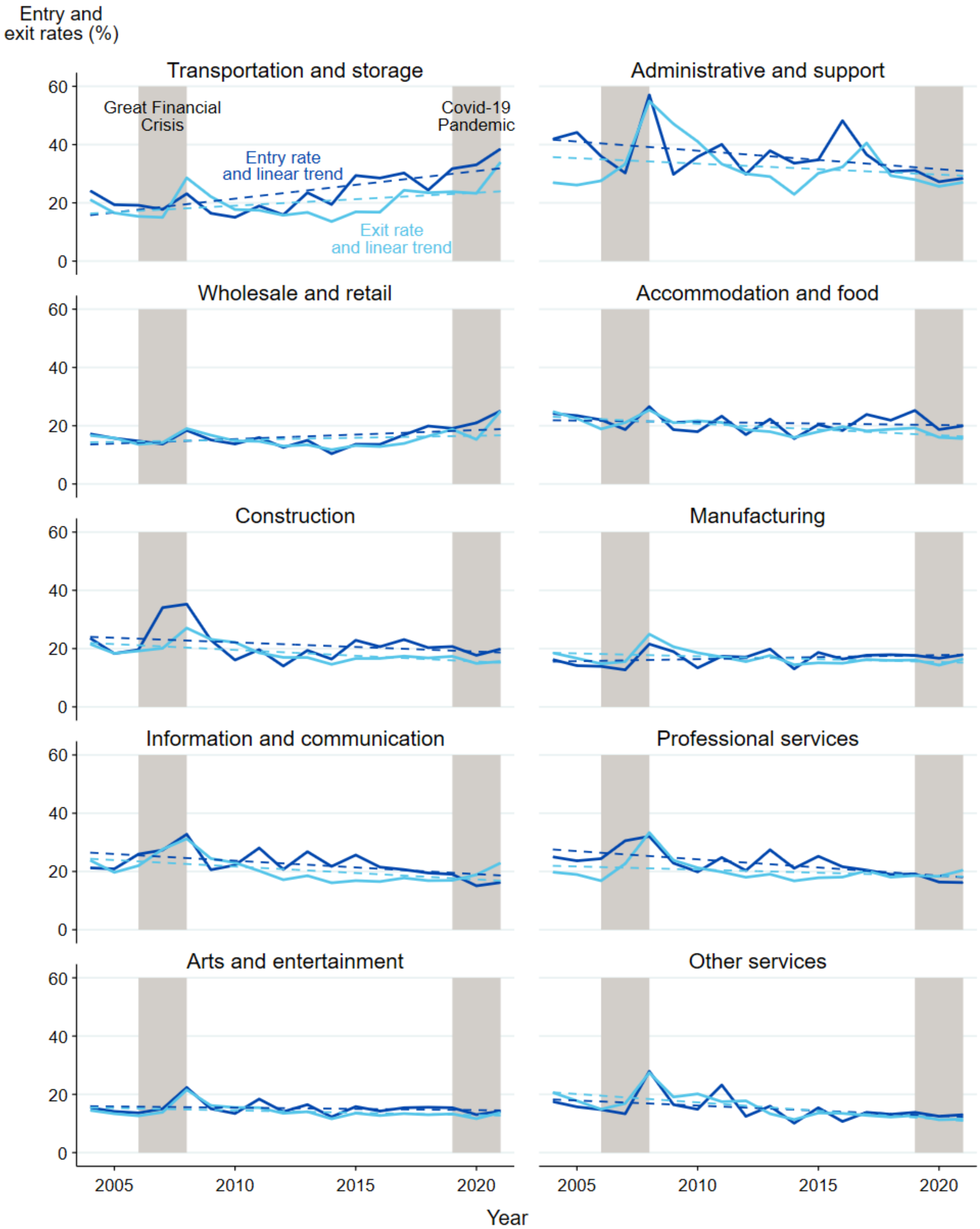
Whole-economy entry and exit rates, from the Longitudinal Business Database (LBD), 2004-2021. UK



Whole-economy entry and exit rates. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2004-2021).

Figure 24: Entry and exit rates in sectors have fallen over time, with few exceptions

Entry and exit rates at Standard Industrial Classification (SIC) industry level, from the Longitudinal Business Database, 2004-2021. UK



Entry and exit rates at Standard Industrial Classification (SIC) industry level. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q,T, U. Industries are ranked by the highest entry rate in 2021. Data from the *Longitudinal Business Database* (2004-2021).

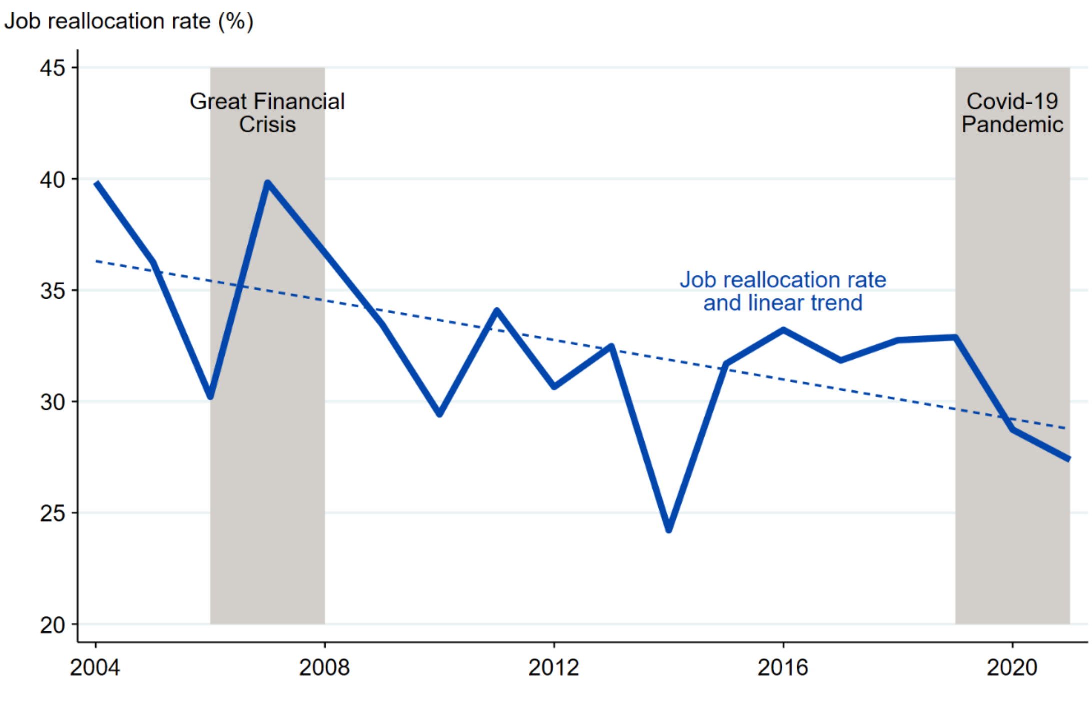
The job reallocation rate has also fallen

4.17 Job reallocation summarises employment flows across firms resulting from job creation (by firms expanding or being born) or job destruction (by firms closing or reducing their size). Therefore, the job reallocation rate is one of the most common measures of business dynamism.

4.18 In the UK, the job reallocation rate (measured relative to the stock of jobs in the economy) has fallen considerably since 2004, as shown in Figure 25. Similar trends are mirrored in most sectors, with the exception once again of transportation and storage. This can be seen in Figure 26.

Figure 25: The job reallocation rate has fallen over time

Whole economy job reallocation rates, from the Longitudinal Business Database, 2004-2021. UK



Whole-economy job reallocation rate. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2004-2021).

4.19 A fall in the job reallocation rate can result from a decline in the job creation rate, the job destruction rate or both. Furthermore, these movements can result from already existing firms (incumbents) expanding or reducing their size by hiring and firing employees, or by entry and exit of firms.

Figure 26: The job reallocation rate declined in all sectors but transportation and storage

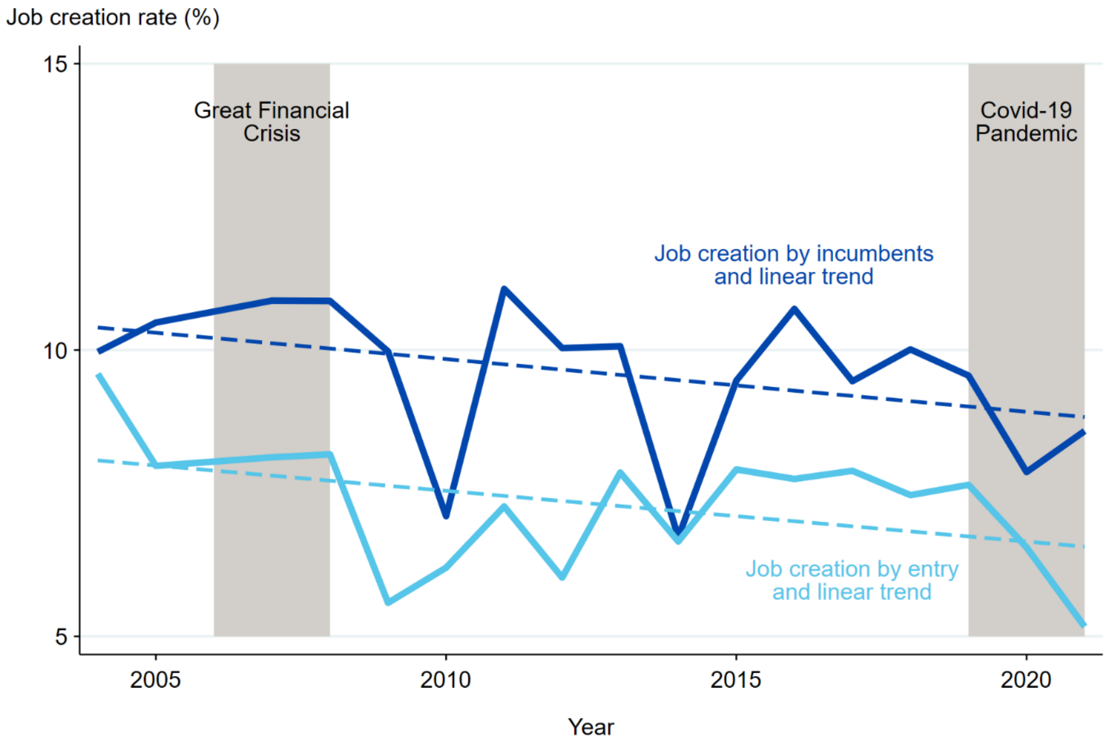
Job reallocation rates at Standard Industrial Classification (SIC) industry level, from the Longitudinal Business Database, 2004-2021. UK

Job reallocation rate at Standard Industrial Classification (SIC) industry level. Industries are ranked by highest job reallocation rate in 2021. Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Data from the *Longitudinal Business Database* (2004-2021).

4.20 In the UK, both the job creation rate and destruction rate have slowed down since 2004. However, the source of the fall differs between the two. As shown in Figure 27, the fall in job creation is due to both a lower entry rate of new firms in the economy and a decline in the job creation rate by incumbents.

Figure 27: There has been a decline in the job creation rate of incumbents and of new entrants

Whole-economy job creation rates, from the Longitudinal Business Database, 2004-2021. UK

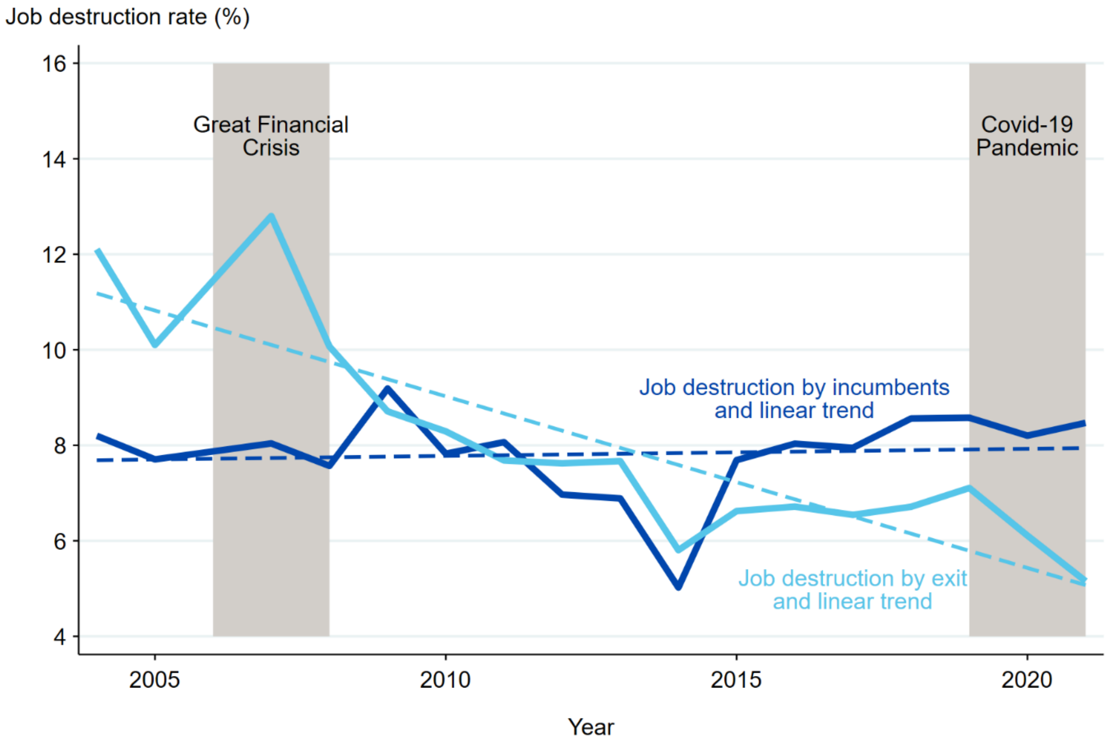


Whole-economy job creation rates. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2004-2021).

4.21 By contrast, the slowdown in the job destruction rate has been caused only by fewer firms dying and exiting, as depicted in Figure 28. The job destruction rate of incumbents has been mostly constant since 2004, with some movement happening between the Great Financial Crisis and 2015.

Figure 28: The decline in the job destruction rate is mainly caused by fewer firms ceasing activity

Whole economy job destruction rates, from the Longitudinal Business Database, 2004-2021. UK



Whole-economy job destruction rates. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2004-2021).

Rank persistence has increased across the economy

4.22 Rank persistence measures what fraction of the largest firms in an industry can maintain their position over an extended period. We can measure persistence both in terms of turnover and in terms of markups.

4.23 In our analysis, we first focus on the top ten firms in terms of turnover in each industry and consider a three-year window. For example, a rank persistence of 0.25 means that a quarter of the firms in the top 10 today were also in the top ten in each of the three previous years.

4.24 In the UK, the average rank persistence has steadily increased over the past twenty-five years, indicating that there is less replacement of firms at the very top. Figure 29 shows this holds true within all sectors individually as well, with arts and entertainment, other services, wholesale and retail, and administrative and support seeing the biggest increase in persistence at the top.

Figure 29: Average persistence has slightly increased in all sectors since 2000

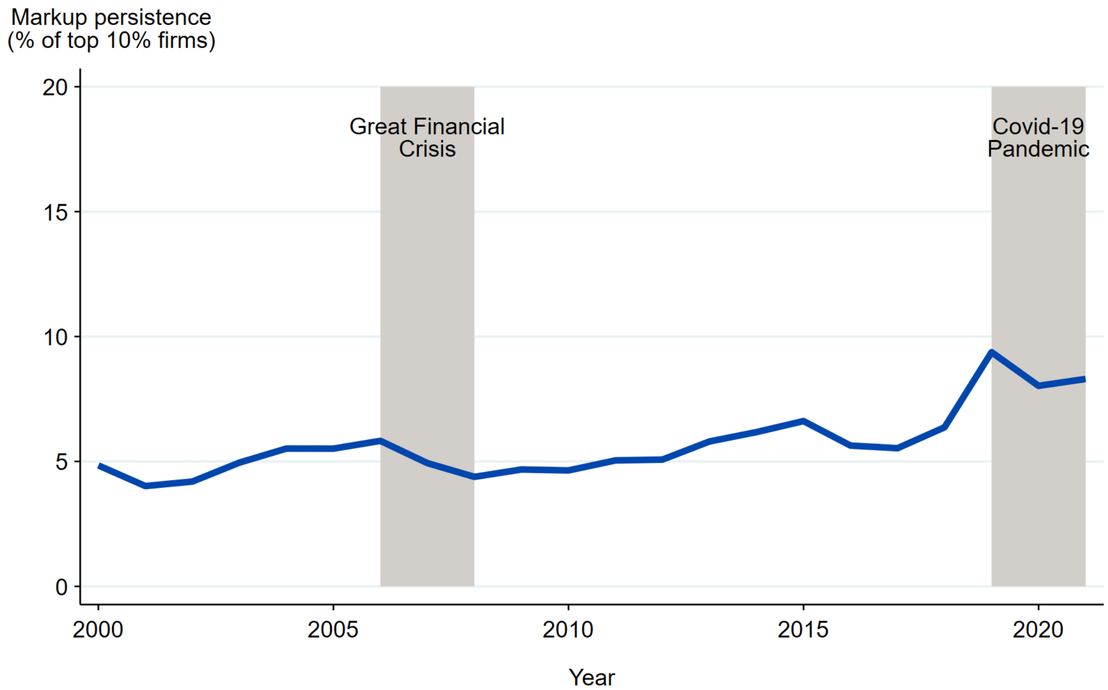
Average sectoral rank persistence of top 10 firms in terms of turnover, from the Business Structure Database, 1997-2022

Persistence defined as the percentage of the 10 highest turnover enterprises that were also in the top 10 in the previous three years. Persistence calculated at 2-digit Standard Industrial Classification (SIC) level and aggregated to sector level using turnover weights. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Industries ranked by size of the increase in persistence over the period. Data from *Business Structure Database* (1997-2022).

4.25 Likewise, we can measure the persistence of firms at the top of the markup distribution within each industry. As Figure 30 shows, the persistence of firms with the highest markups has also increased over time. An additional figure in the appendix, Figure E.10, shows that there is significant variation across industries in the rise of markup persistence, with services contributing significantly to the overall rise.

Figure 30: The persistence of high-markup firms markups stayed constant until the mid-2010s and but has increased in recent years

Whole-economy persistence of firms at top 10% of markup distribution, from the Business Structure Database, 1997-2022



Persistence defined as percentage of firms (reporting units) in the top 10% of markup distribution that were in the top 10% also in the previous three years. Persistence calculated in each Standard Industrial Classification (SIC) industry and aggregated using turnover weights. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Business Structure Database* (1998-2022).

4.26 These trends are in line with those of entry, exit and job reallocation rates. Together, they signal that the UK economy has become less dynamic over time.

Markups and business dynamism are unrelated across industries

4.27 This report has shown that across the whole economy, average markups have increased, and business dynamism has fallen. If the two phenomena are related, we would expect them to be negatively correlated at the industry level as well. This section therefore examines the relationship between markups and business dynamism at the industry level.

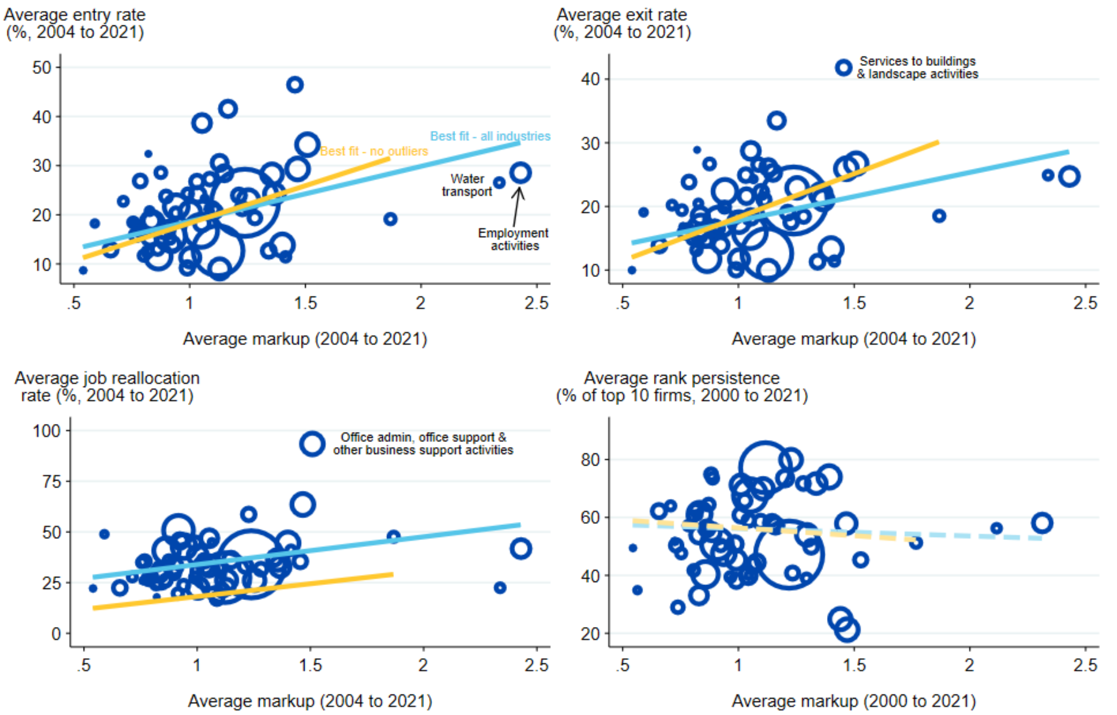
4.28 A plausible hypothesis is that industries where markups are higher also have lower business dynamism. This could indicate a lack of competition, whereby firms with market power use their position to prevent the entry of new firms and the reallocation of economic activity.

4.29 Alternatively, high markups may tempt new firms to enter the market, hoping to earn profits. This is what standard economic theory might predict.

4.30 Figure 31 shows across four panels that markups and our four baseline measures of business dynamism at the two-digit industry level are generally positively correlated. The four measures are firm entry and exit rates, job reallocation rates and rank persistence.

Figure 31: Markups and business dynamism are positively correlated

Standard Industrial Classification (SIC) industry level scatterplot between four business dynamism measures and markups, 2004-2021, from the Annual Respondents Database X (1997-2020), the Annual Business Survey (2021) *and Longitudinal Business Database (2004-2021)*



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Lines of best fit weighted by turnover and statistically significant at the 5% level (represented by the solid lines), with the exception of the fourth panel (dashed lines). Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), the *Business Structure Database* (1997-2021) and the *Longitudinal Business Database* (2004-2021).

4.31 Markups are slightly positively related to firm exit and entry rates and job reallocation rates and unrelated to rank persistence.

4.32 This finding is consistent with the patterns Albrecht and Decker (2024) find for the US and suggests that the rise in markups (and any associated increase in entry barriers) is unlikely to be the primary driver behind the fall in business dynamism.

The contribution of young firms has declined

4.33 A large strand of research highlights the importance of young firms in introducing new ideas, processes, and technologies into the economy (Foster, Haltiwanger and Syverson, 2005; Haltiwanger, Jarmin and Miranda, 2013). In this section, we look at the contribution to overall turnover and employment by young firms, defined here as those established fewer than five years prior. We find that the turnover and employment share of young firms in the UK has also declined over the past two decades.

4.34 We use both establishments (physical sites, or "local units" in the language of the Office for National Statistics) and enterprises (standalone legal entities) to measure employment shares of young firms. For most firms, the establishment and enterprise will be the same, as they only have one physical site.

4.35 However, while the number of multi-establishment enterprises is much smaller, they account for a disproportionate share of turnover and employment. Since turnover is not observed at the establishment level, we only report the turnover share at the enterprise level.

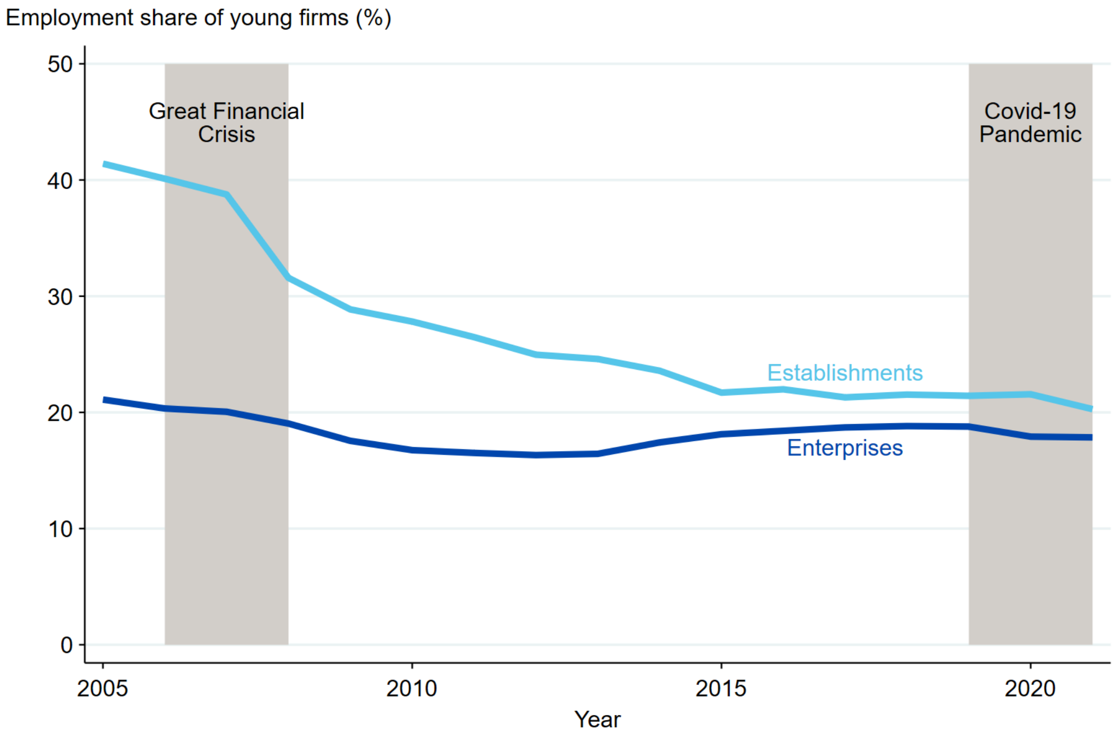
4.36 Figure 32 shows that over the last two decades, the employment share of young establishments has fallen from 40% to 20%. The steepest fall occurred during the Great Financial Crisis.

4.37 By contrast, the employment share of young enterprises has shown a much smaller decline until 2013 and has mostly recovered since. This indicates that most of the fall in the employment share of young establishments comes from a slowdown in the expansion of existing multi-establishment firms rather than new standalone enterprises.

4.38 Figure 33 shows that the turnover share of young enterprises has likewise fallen, from 18% in 2005 to 10% in 2021. Again, most of the fall is accounted for by the Great Financial Crisis and its immediate aftermath.

Figure 32: The employment share of young establishments has fallen, while the employment share of young enterprises has stayed constant

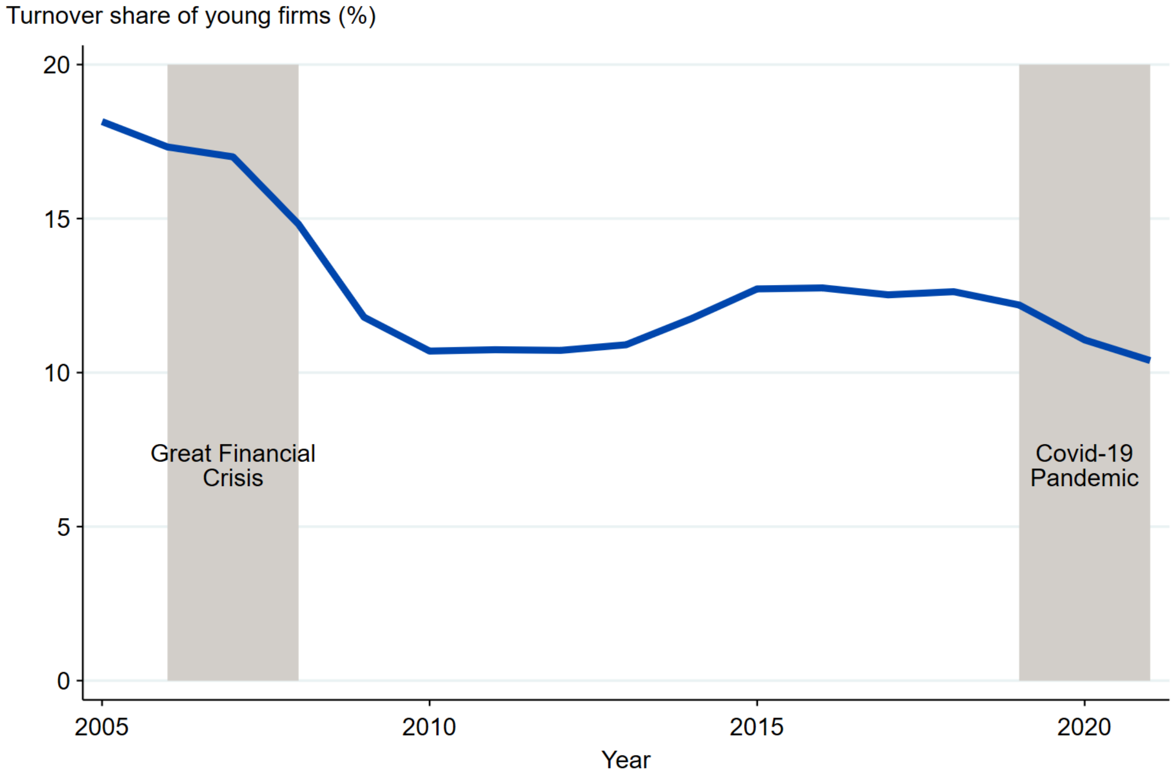
Employment share of establishments and enterprises less than 5 years old. Age of establishments and enterprises estimated using the year of first appearance on the Longitudinal Business Database. Data from the Longitudinal Business Database, 2005-2021. UK



Employment share of enterprises and establishments younger than 5 years old. Age of enterprises and establishments estimated using the year of first appearance on the *Longitudinal Business Database*. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2005-2021).

Figure 33: The turnover share of young enterprises has halved since 2005

Turnover share of enterprises less than 5 years old. Age of establishments and enterprises estimated using the year of first appearance on the Longitudinal Business Database. Data from the Longitudinal Business Database, 2005-2021. UK



Turnover share of enterprises younger than 5 years old. Age of enterprises estimated using the year of first appearance on the *Longitudinal Business Database*. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2005-2021).

Academic research around the world finds similar trends

4.39 Lui, Black, Lavandero-Mason and Shafat (2020) document a decline in UK aggregate business dynamism since the 2008 economic downturn. Both job destruction and job creation triggered by entry have declined. Oliveira-Cunha, Kozler, Shah, Thwaites and Valero (2021) similarly find that productivity growth of UK businesses has slowed down across sectors since the Great Financial Crisis, and more so than in Germany, France, or the US. The aggregate job reallocation rate is however found to be broadly stable since the early 2000s in positive contrast to France and the US.

4.40 Kim and Savagar (2023) differ from most other studies by finding stable levels of entry and exit over the period between 1997 and 2020. This is due to a different, more stringent definition of firm activity. Allocative efficiency, which captures the extent to which workers are allocated to more productive firms, improved until the mid-2010s but has declined since, particularly among high allocative-efficiency industries.

4.41 Lui, Black, Lavandero-Mason and Shafat (2020) find that age plays a crucial role in the UK's business dynamism. Young firms constitute the most dynamic group of firms, independently of size.

4.42 Anyadike-Danes, Hart and Du (2015), using data on job-creating businesses in the UK between 2007 and 2010, find that young and typically small firms play an important role in employment creation. They estimate that every year a cohort of between 200,000 and 250,000 new private firms are born, creating about one million jobs. A decade later, while approximately three quarters of these firms will have disappeared, the surviving businesses will employ about half a million workers.

4.43 It is widely recognised that there has been a decline in US business dynamism in the past two decades (Akcigit and Ates, 2021; Decker, Haltiwanger, Jarmin and Miranda, 2015), only recently reversed due to a post-pandemic boom in entrepreneurial activity (Decker and Haltiwanger, 2023).

4.44 Haltiwanger (2015) documents a substantial decline in measures of business dynamism in the US since the mid-1980s, which accelerated after the year 2000. Prior to 2000, the decline in business dynamism was primarily limited to retail trade and service sectors while sectors such as high tech and publicly traded businesses exhibited rising dynamism. Since 2000, the latter sectors have also declined in dynamism.

4.45 This decline has been sufficiently significant to lead to a negative net entry rate in recent years. According to the same study, the decline in the share of activity accounted for by young businesses explains a large portion of the decline in US business dynamism.

4.46 Decker, Haltiwanger, Jarmin and Miranda (2014) find that young US businesses exhibit an "up or out" dynamic. If they survive, young businesses have higher rates of job growth than more mature businesses, but young businesses also have substantially higher attrition rates. As in the UK, cohorts of startups make a long-lasting contribution to net job creation. Five years after the entry of a cohort, total employment by firms in that cohort is approximately 80% of the original employment contribution of the cohort, despite 50% of the original employment being lost through business exits.

4.47 Biondi, Inferrera, Mertens and Miranda (2024) study business dynamism in Europe after 2000 using data from nineteen countries, including the UK. They find a broad decline in job reallocation rates, taking place across most economic sectors and countries. Large and older firms exhibit the most intense decline. The importance of young firms, both in terms of employment and turnover shares, is declining.

4.48 Calvino, Criscuolo and Verlhac (2020) analyse international trends in business entry and exit rates as well as job reallocation rates, studying twenty-two sectors in eighteen countries (excluding the US and the UK) between 2000 and 2015. Echoing UK findings, they find that many countries have witnessed a decline in business dynamism, though there is significant variation across and within countries.

4.49 The decline in business dynamism is more pronounced in sectors characterised by a higher importance of intangibles and digital technologies as well as higher concentration and productivity dispersion. Overall, business dynamism thus appears to be negatively affected by the presence of established leaders in industries with high investment in information technologies.

5 UK market power in international perspective

5.1 The previous chapters have described trends in UK market power and concentration over the last twenty-five years. This chapter puts the UK figures in the context of peer economies on available measures.

5.2 This serves two purposes: first, it provides context for the size of the changes we see in the UK. Second, identifying whether trends are common or UK-specific speaks to the root causes of the rise in market power. The next chapter will explore these causes in more detail.

5.3 We find that the UK has seen very similar trends in markups, concentration, firm entry and exit to comparable European countries. This suggests that the drivers of these trends are likely not specific to the UK.

5.4 The cross-country comparison is made possible by the Competitiveness Research Network (CompNet) distributed microdata project at the Leibniz-Institut für Wirtschaftsforschung Halle (IWH).

5.5 While this data collection and standardisation effort is invaluable for policy analysis, two caveats are worth mentioning. First, the results in this chapter have been produced with CompNet code. They may therefore not match results elsewhere in the report exactly.

5.6 Second, data sources differ somewhat across countries: in some cases, they are derived from survey sources, in others from administrative data. This may account for some of the cross-country differences.

5.7 We omit three countries from the comparison because they are substantial outliers on at least one of the measures: These countries are Finland, France, and Sweden. For example, markups in France are much higher than markups of comparable countries in the CompNet dataset.

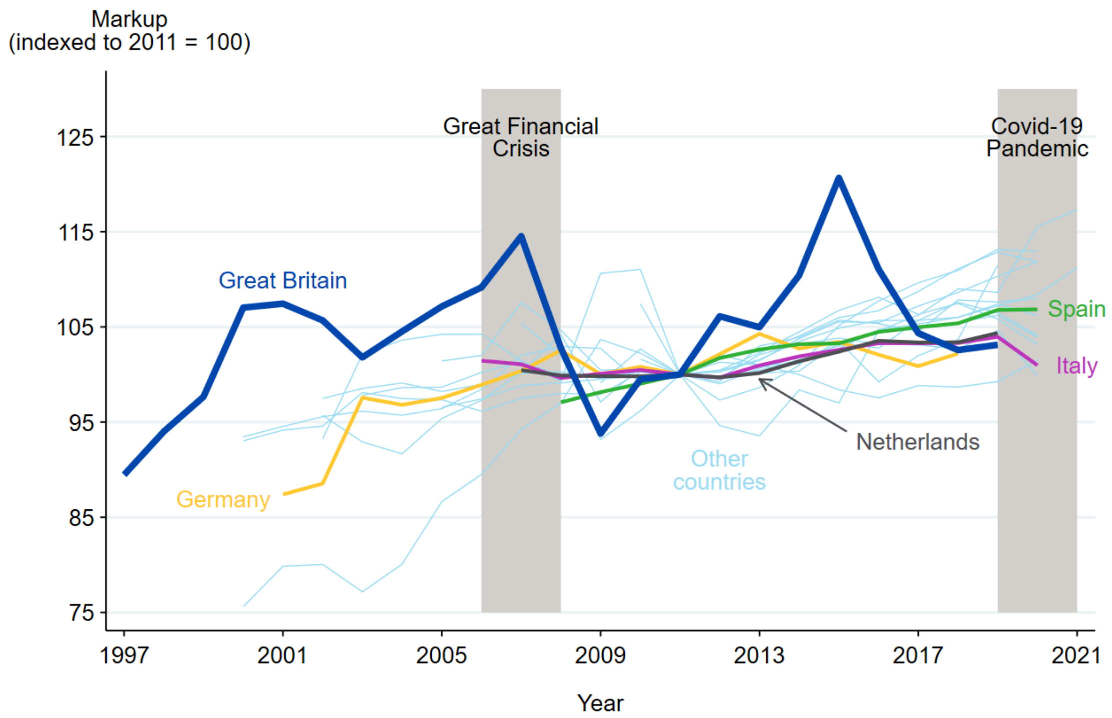
5.8 CompNet markups for Great Britain show substantial variability over time but are nonetheless included to enable international comparisons. However, the results elsewhere in this report should be seen as more reliable.

Other European countries see similar trends

5.9 Figure 34 plots GB markups against those of comparison countries, with levels indexed to 100 in 2008 for comparison. Germany, Italy, Spain, Belgium and the Netherlands all see similar trends to Great Britain. Cumulatively, the markup change is slightly lower in the UK than in comparable countries.

Figure 34: GB markup trends are similar to those of peer economies

Economy-wide average markup estimates, ordinary least squares estimation of a translog production function, data from the Competitiveness Research Network (CompNet), 1997-2021



Markup estimated using production function approach. Ordinary Least Square estimation of a translog production function, with materials as flexible input. Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

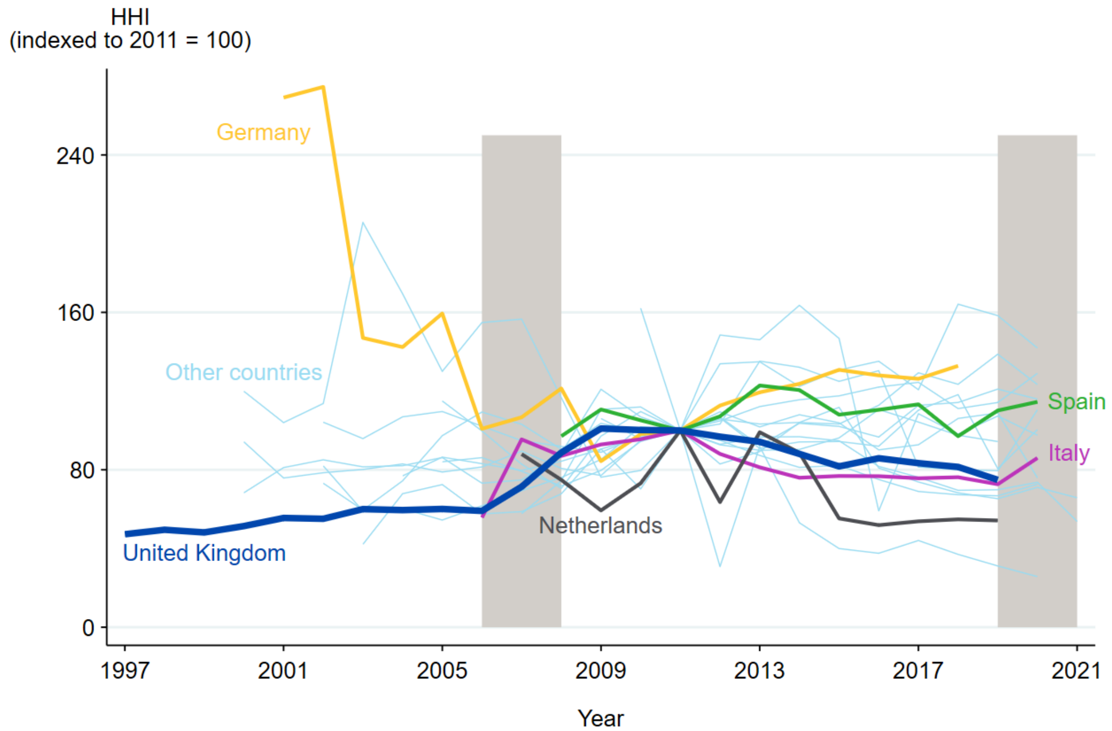
5.10 Figure E.19 in the appendix plots markup levels for the same countries. Markups appear consistently higher in Great Britain but have not risen as much. Aggregate markup levels in Germany appear similar but see less pronounced changes over time.

5.11 Figure 35 plots concentration levels across the same set of countries, again indexed to 100 in 2008. When comparing changes in concentration over time, the UK finds itself in the middle of the pack when compared to European peers.

5.12 Finally, Figure 36 plots the indexed job creation (panel 1) and destruction rates (panel 2) for the UK against the same set of comparator countries. For both, the UK has a considerably longer time series but for overlapping years trends mirror those of peer European countries.

Figure 35: Concentration trends in the UK are similar to other European countries

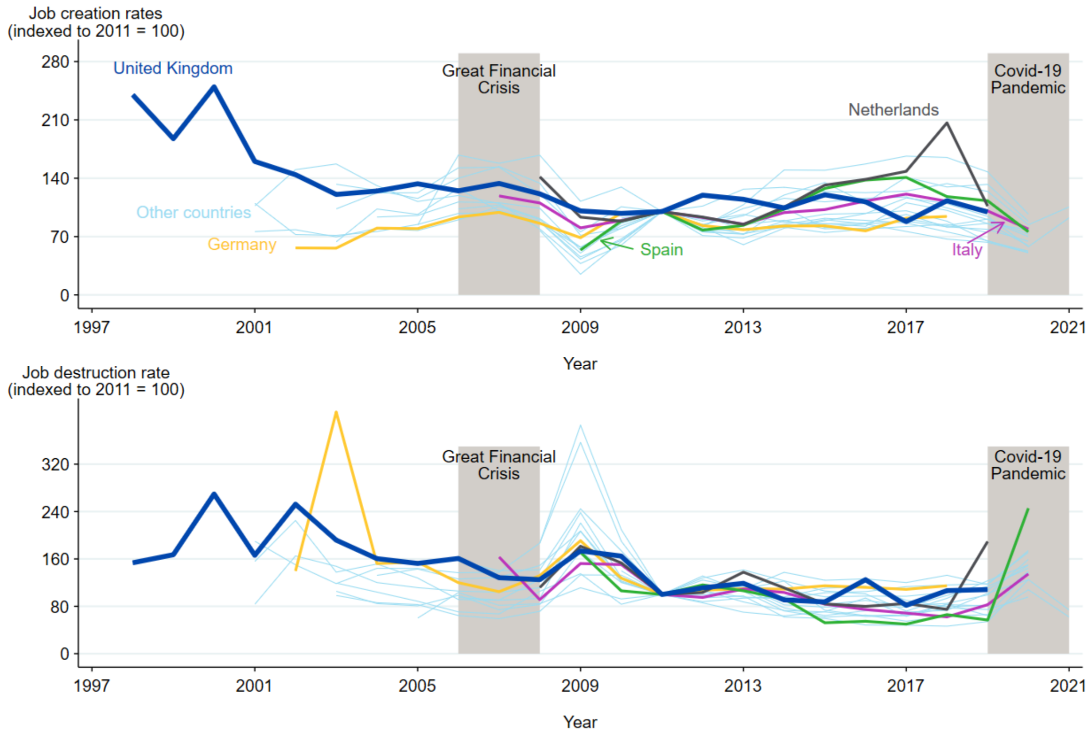
Economy wide mean Herfindahl-Hirschman Index, data from the Competitiveness Research Network (CompNet), 1997-2021



Estimates of Herfindahl-Hirschman Index (HHI). Other countries include: Belgium, Croatia, Czech Republic, Denmark, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Figure 36: Job creation rates have been stagnant while job destruction rates have fallen across European countries

Economy wide estimates of job creation and job destruction rates, data from the Competitiveness Research Network (CompNet), 1997-2021. UK



Estimates of job creation and destruction rates. Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Existing studies find similar results for the US

5.13 Because the US is not included in the CompNet dataset, we cannot make the same direct comparison to the UK. However, many academic studies find similar results for the US, using similar methods and data sources.

5.14 Most studies find an increase in markups between the mid-nineties and the late 2010s of somewhere between 2-30%. A period of steep increase in markups since 1980 was followed by a period of stagnation between 2000-2010, followed by a further increase since.

5.15 De Loecker, Eeckhout and Unger (2020) find that US average markups grew from 1.37 to 1.61 (an 18% increase) between 1995 and 2016. De Loecker, Eeckhout and Mongey (2022) find an increase from 1.42 to 1.8 between 1995 and 2018 (a 27% increase). Diez, Leigh and Tambunlertchai (2018) find an increase from 1.23 in 1995 to 1.6 in 2015 (a 30% increase).

5.16 Most other estimates are significantly smaller. Cavalleri, Eliet, McAdam, Petroulakis, Soares and Vansteenkiste (2019) find US average markups grew from 1.2 to 1.23 between 1995 and 2015. Traina (2018) also finds that the rise in markups is more muted when accounting for measurement error. He finds that markups rise from only 1.15 to 1.17 between 1995 and 2016. Similarly, Vlokhoven (2023) finds an increase from 1.28 to 1.33 from 1995 to 2015.

5.17 Ugur (2023) calculates two different markup measures, rising from 1.15 to 1.2 and from 1.25 to 1.32 between 1995 and 2019.

5.18 The overall US trend masks significant variation across and within sectors, as documented by De Loecker, Eeckhout and Unger (2020) and echoed by Autor, Dorn, Katz, Patterson, Van Reenen (2020).

5.19 De Loecker, Eeckhout and Unger (2020) find that the increase in aggregate markups is driven by a few large firms, while most firms see no increase in their markups. Comparing the distribution of markups in 1980 and 2016, the latter has the same median as the former but a higher standard deviation and more high-markup firms in the upper tail of the distribution.

5.20 The change in sales weighted average markup can be decomposed into three components: a between-firm channel (reallocation among firms that stay active so that firms with higher markups get more sales), a within-firm channel (firms increase their own markup) and a net-entry channel (entering firms have higher markups than exiting firms).

5.21 De Loecker, Eeckhout and Unger (2020) find that the between-firm channel alone accounts for two thirds of the change over the entire period from 1980-2016. Farhi and Baqaee (2020) come to the same conclusion.

5.22 By contrast, this report finds that within-sector increases account for the majority of the rise in UK markups. Of course, some of the within-sector increases may be due to between-firm reallocation within the same sector. Due to the way in which the UK's Annual Business Survey is sampled, we cannot currently test this theory.

5.23 De Loecker, Eeckhout and Unger (2020) find similar dynamics in all sectors, which all exhibit similar increases in markups and the same reallocation of market shares between low- and high-markup firms. Diez, Leigh and Tambunlertchai (2018) also conclude that markups have increased across all major industries, not only high-tech industries.

5.24 There is slightly more debate about aggregate trends in Europe, where estimates of the rise in markups range from -4 to 23%.

5.25 De Loecker and Eeckhout (2021) find that aggregate markups in Europe (including the UK) have increased from 1.3 to 1.6 between 1980 and 2016 (a 23% increase). Calligaris, Chaves, Criscuolo, De Lyon, Greppi and Pallanch (2024) examine data covering many EU countries and the UK for the period 2000-2019 and find that average markups have increased by 7% over that period. Diez, Leigh and Tambunlertchai (2018) find an increase in average markups for European advanced economies (including the UK) from 1.1. in 1995 to 1.3 in 2015 (an 18% increase).

5.26 Two large studies which use a different, accounting-based measure of markups instead find a mild decline. Cavalleri, Eliet, McAdam, Petroulakis, Soares and Vansteenkiste (2019) analysing a group of countries that belong to the EU single market (including Germany, France, Spain, and Italy) find that the aggregate markup has been stable and even slightly declined from 1.18 in 1995 to 1.13 in 2015.

5.27 Ugur (2023) also finds evidence of a slightly decreasing trend between 1995 and 2019 in France, Italy, Spain and Germany. The difference to the rest of the literature is likely driven by the difference in how markups are defined and measured in these two studies.

5.28 In terms of variation in markups across firms, De Loecker and Eeckhout (2021) find that in Europe, as in the UK and US, the change in markups is driven by the upper tail of the distribution, with only a few firms seeing an increase in their markups.

5.29 However, they find no evidence in the EU of the "superstar firm" theory at play, which speculates that a few highly productive firms with both high and increasing markups and market shares drive the increase. This contrasts with US evidence. For the EU, they find that none of the increase in sales weighted average markups stems from sales reallocation towards higher markup firms. Cavalleri, Eliet, McAdam, Petroulakis, Soares and Vansteenkiste (2019) similarly find little evidence of the emergence of superstar firms.

5.30 Finally, Mertens and Mottironi (2023), studying data from 19 European countries, even find that larger firms have lower markups within narrowly defined industries and product markets. The findings, seemingly at odds with existing results by Autor, Dorn, Katz, Patterson and Van Reenen (2020) and De Loecker, Eeckhout and Unger (2020), can be reconciled when accounting for the labour market power these firms exercise.

5.31 In line with supplementary results in this study, the CMA's recent report on labour market power finds that wage markdowns and materials markups are negatively correlated at the firm level (CMA, 2024), indicating that similar dynamics may be relevant for the UK. This remains an important area of further study.

5.32 Overall, research from around the world replicates the broad findings this report documents for the UK. This suggests a common, structural cause. Nonetheless, estimates vary considerably across and within countries, which may hold important lessons for policymakers.

6 Possible drivers of the rise in market power

6.1 There are many explanations for why markups and concentration may be rising, but two are by far the most common.

6.2 The first is a story of technological change. Firms are becoming more intangible capital-intensive, which means they need to invest upfront in fixed costs such as R&D, software, and branding.

6.3 However, this investment makes it cheaper to produce each additional unit (for example, because an increasing share of consumer goods consists of software components, which can be reproduced at zero cost). As a result, innovative firms become larger and markets more concentrated, producing goods more cheaply and at greater scale.

6.4 While this development is also possible with tangible capital such as land or machinery, intangible capital can be deployed at much greater scale and essentially zero marginal cost (Haskel and Westlake, 2022).

6.5 For instance, Calligaris, Criscuolo and Marcolin (2024) show that new digital business models rely on the intensive use of knowledge assets whose marginal cost of replication is very low, thereby achieving economies of scope in data collection and analysis.

6.6 At the same time as knowledge assets have become more important, many authors argue that barriers to the diffusion of knowledge across firms have grown as well. Akcigit and Ates (2019; 2023), while stressing the importance of firm investment in productivity, emphasise that it has become more difficult for technologically inferior firms to catch up technologically. They attribute the decline in diffusion to a more intense use of intellectual property protection and proprietary data.

6.7 Calligaris, Criscuolo and Marcolin (2024) and Covarrubias, Gutiérrez, and Philippon (2020) similarly argue that combinatorial innovation processes (whereby innovative firms build on other firms' innovations) are becoming increasingly important, and stress that much of the knowledge is often protected by intellectual property rights that limit access and use.

6.8 Firms may also employ other diffusion-inhibiting strategies. These include litigation, the use of patent "thickets" (many closely related patents issued to deter innovation, as detailed for instance by Jaffe and Lerner, 2006) or "killer acquisitions" of startups (an acquisition with the purpose of killing off a competing technology, as argued by Cunningham, Ederer and Ma (2021)).

6.9 Direct and indirect network effects can be very strong in digital industries, where platforms play a very central role. These effects naturally advantage larger players who offer higher value to customers by the sheer fact of having more users.

6.10 Google, for example, delivers more accurate search results because it has more users, thereby training its algorithm on larger data sets. Chapter 3 of the CMA's final report on digital advertising includes evidence that a larger share of Google's search queries than Bing's is unique (CMA, 2020). Similarly, Amazon is attractive to each side of the market (buyers or sellers) because of the larger number of participants that it attracts on the other side of the market.

6.11 De Loecker, Obermeier and Van Reenen (2022) however caution that the big platforms still account for a relatively small proportion of the economy in the US, UK or EU. High tech industries account for 23% of the US economy and only 7.7% of the UK economy, so platform-related dynamics alone cannot explain aggregate markup trends.

6.12 Consumers may also have become more sensitive to price or quality due to improved search and price comparison technologies, which benefits firms who have a slight original advantage in productivity (Autor, Dorn, Katz, Patterson and Van Reenen, 2020), prices or quality, or in their ability to use data to engage in price or product differentiation (Calligaris, Criscuolo and Marcolin, 2024).

6.13 Overall, there is still a lively debate as to how to interpret these technology-related changes in terms of market power implications. Does this technology-driven reallocation of economic activity towards larger firms embody a well-functioning competitive process that has naturally tilted towards more "winner takes most" outcomes (Autor, Dorn, Katz, Patterson and Van Reenen, 2020)? Or does it instead represent an increase in market power driven by increased technological entry barriers?

6.14 Covarrubias, Gutiérrez, and Philippon (2020), referring to this distinction, speak of "good" versus "bad" competition. They find that most US industries were becoming more concentrated because of pro-competitive forces in 1997 but that the balance had shifted to anti-competitive forces by 2012.

6.15 Along similar lines, De Loecker, Eeckhout and Unger (2020) find evidence that since the 1980s, firms have become more profitable (the average profit rate rising from 1% to 8% between 1980 and 2016) and generate higher returns for stakeholders (as captured by market value and dividends). They find that while an increase in fixed costs provides part of the explanation for increased markups, firms charge an excess markup that more than compensates for their fixed costs. They therefore conclude that firms' market power has increased.

6.16 This dovetails with the second common explanation of markups as a story of rising pricing power and weakening competition. According to this theory, markets are becoming more concentrated because of mergers and acquisitions and because incumbents build barriers that make it harder for new firms to enter.

6.17 Some economists argue that competition agencies are not able to combat this rise in anti-competitive conduct, either because they are outmatched by the resources merging companies have at their disposal, or because courts and policymakers have adopted a more laissez-faire approach. As a result, consumers face higher prices, lower quality, and less product variety.

6.18 Lancieri, Posner and Zingales (2023) present evidence that antitrust enforcement in the United States has declined significantly since the 1960s. For example, Department of Justice (DoJ) antitrust lawsuits dropped from one hundred per year in the early 1980s to slightly above twenty-five per year in 2018. Similarly, the number of mergers that are challenged by regulators has dropped significantly since the 1990s.

6.19 Wollmann (2019) focuses on the phenomenon of "stealth consolidation", whereby large numbers of small mergers in very segmented industries can cumulatively have a large impact on market power in an industry. He focuses on a change in US merger review rules implemented in 2000 which significantly increased the size requirement for an investigation to be launched by antitrust authorities. The change led to a very significant increase in realised mergers, both by decreasing the number of blocked merger projects and by boosting the number of merger applications.

6.20 Gutiérrez and Philippon (2018) argue that, unlike US enforcement, EU enforcement has improved in recent decades. They point, for instance, to the relative position of the EU in international competition enforcement indexes, and note that relative to the US, EU enforcement numbers have risen. They also observe that, compared to a few decades ago, the EU now also has a single EU-wide competition agency (the Directorate-General for Competition, or DG-COMP) endowed with significant powers and autonomy.

6.21 Despite differences in competition enforcement across jurisdictions, international markup trends have been similar. This suggests that differences in competition enforcement are not solely responsible for the observed markup trends.

6.22 The technology and "pricing power" explanations need not be mutually exclusive: for instance, platforms and software may both make it easier to produce new goods faster and more cheaply and allow firms to erect barriers against new entrants. In this chapter, we provide some tentative evidence that suggests the technology explanation is at least in part responsible for the rise in UK markups. This chimes with recent work by Miller (2024) and Shapiro and Yurukoglu (2024) who for the US likewise argue that evidence for the "pricing power" explanation is less strong than previously claimed.

6.23 Finally, while technology and antitrust enforcement have received the most attention as explanations of the increase in markups, other factors have also been proposed. These include a potential increase in the amount of common ownership of rival firms by financial intermediaries, which could be conjectured to weaken individual firms' incentive to compete, and the process of globalisation, which could decrease marginal costs by allowing firms to access cheaper inputs and greater economies of scale.

6.24 De Loecker and Eeckhout and Mongey (2021), study markups at the four-digit industry level and find a decrease in industries facing stronger competition from Chinese imports. This is consistent with the UK findings in this report.

Fixed costs have become more important, material inputs less so

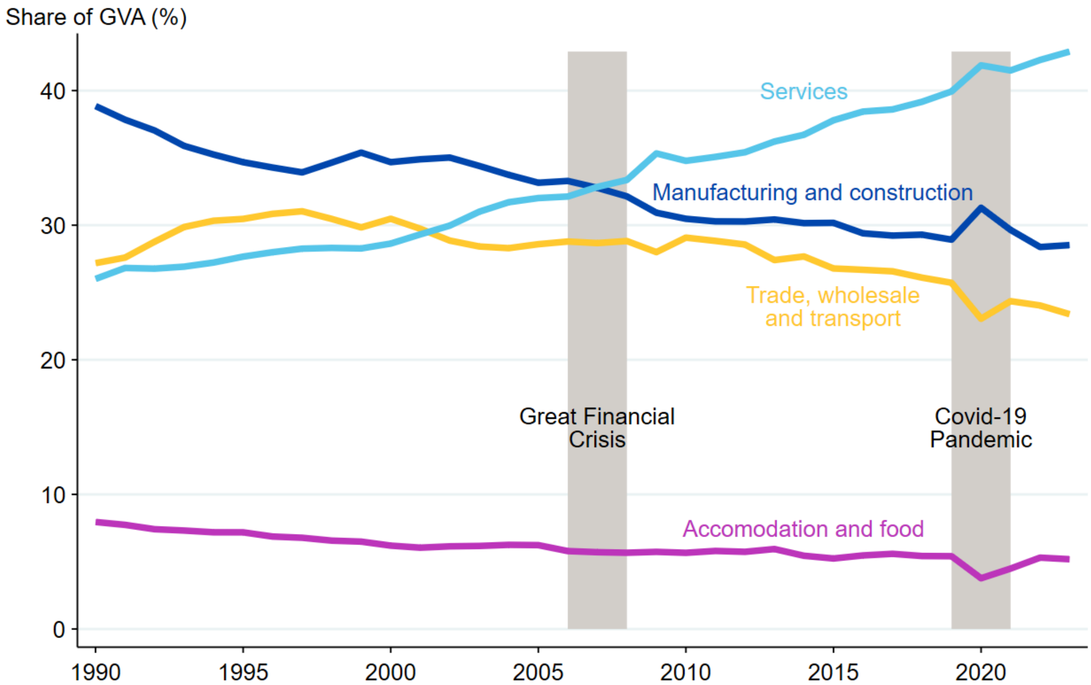
6.25 This section presents evidence on the extent to which technological changes may have contributed to the rise in average markups. We show that overall, over the past twenty-five years, the UK economy has moved further from manufacturing into services. We also show that the responsiveness of output to different types of input has changed in ways that are consistent with a move towards a more intangible economy. We show that our best available estimates of fixed costs have increased over time, before dropping rapidly in the Covid-19 pandemic. Finally, we show that estimates of returns to scale have increased in parts of the service sector, but not elsewhere.

6.26 At the macroeconomic level, the economic experience of the UK in recent decades is still one of deindustrialisation. As Figure 37 shows, the share of economy-wide gross value added in manufacturing and construction has decreased from over 40% in 1990 to less than 30% in 2023. Meanwhile, the service share has increased from less than 30% to over 40%. This rise in services shows no sign of slowing down.

6.27 As Haskel and Westlake (2022) have argued, services are particularly amenable to intangible investments like software, branding and R&D that require a large upfront outlay but can then be applied at scale at almost zero marginal cost.

Figure 37: The services share of the UK economy has risen since 1990, while the manufacturing share has declined

Broad sector share of Gross Value Added (GVA) in constant prices, from ONS GDP Output Approach dataset, UK, 1990-2023



Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T and U. Source: *Office for National Statistics GDP output approach – low-level aggregates* (1990-2023)

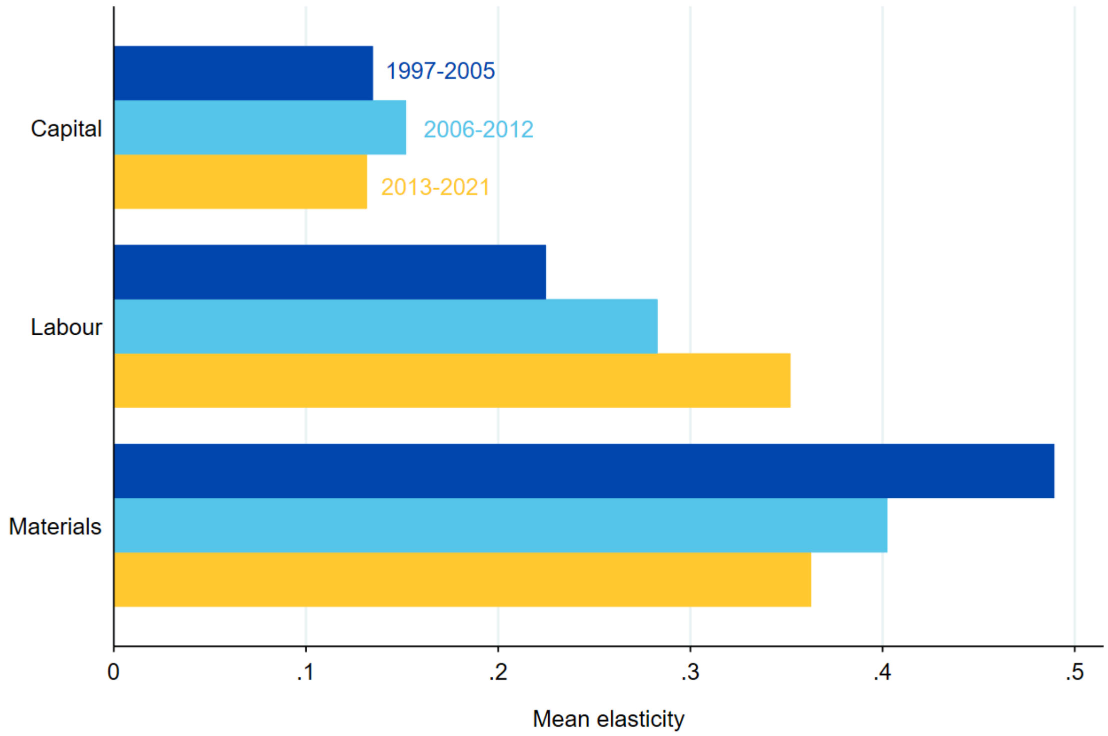
6.28 At the same time, the technologies employed to produce goods and services have changed too. As Figure 38 shows, over time the production technologies the UK employs to produce goods and services have become more sensitive to labour and less sensitive to material inputs.

6.29 Figure 38 shows that the average materials elasticity has decreased, while the average labour elasticity has increased. In other words, on average, an increase in raw material inputs now leads to a smaller increase in output than it did around the turn of the millennium, and an increase in labour now leads to a larger increase. Figure E.28 in the appendix shows that the variance in labour elasticities has also increased, meaning that firms are now more different from each other in how much labour contributes to an increase in output.

6.30 These trends also hold true in the majority of two-digit SIC industries, where within-industry average material elasticities are declining, and labour elasticities are broadly increasing over time.

Figure 38: The average material elasticity has declined

Mean of capital, labour and materials elasticities. The elasticities result from an Ordinary Least Square estimation of a translog production function, as per our baseline approach to markup estimation. Data from Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey (ABS) 2021. GB only



The elasticities result from an Ordinary Least Square estimation of a translog production function, as per our baseline approach described in the report. The analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Data from the *Annual Respondents Database X* (1997-2020) and the *Annual Business Survey* (2021).

6.31 Since these elasticities are a key component of markups, these technological changes will be reflected in our markup estimates too. Additionally, if technological progress is not factor-neutral, but is for instance labour-augmenting, this would be reflected in these input elasticities.

6.32 Some academic studies have tried to look directly at evidence that firms are now spending more on fixed costs. This could explain the rise in average markups, as markups are needed to cover fixed costs, in addition to paying profits to the firm's owners.

6.33 A widely used proxy for fixed costs is Selling, General and Administrative expenses (SG&A) which represent salaries, advertising, rent (selling), general operating expenses, and administrative costs (De Loecker, Eeckhout and Unger (2020)). In line with these studies, we use Bureau van Dijk's FAME database to compute SG&A as a share of turnover (that is, the fixed cost share) for all active UK companies with non-missing data for employees, turnover, and profit (or loss) before interest paid (EBIT) between 2005 and 2021.

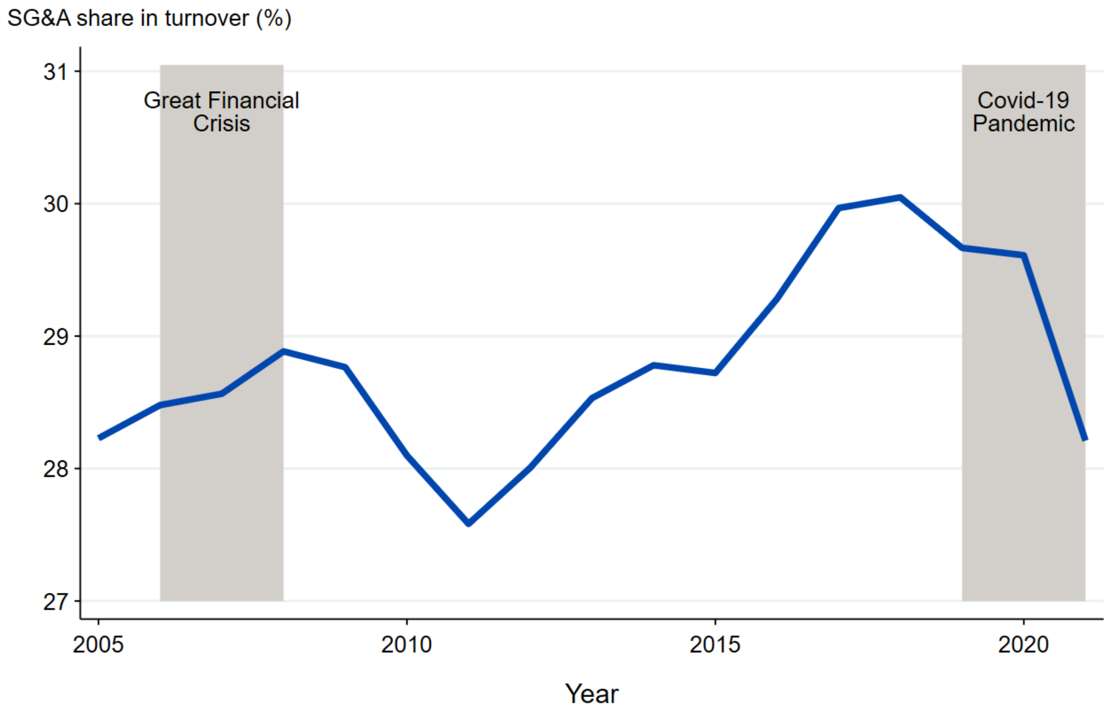
6.34 Due to differences in accounting practices and company policies, there are huge variations in the reporting of SG&A expenses on financial statements across firms. To navigate these challenges, we opt for a simplified approximation method for estimating SG&A expenses.

6.35 We calculate SG&A as gross profit less earnings before interest, taxes, depreciation, and amortization (EBITDA). Dividing this figure by turnover yields our estimated fixed cost share. We remove any firms with shares greater than one.

6.36 Figure 39 plots the unweighted average SG&A by year. In the years leading up to the Covid-19 pandemic, the share of SG&A to turnover has increased steadily year by year, followed by a steep drop since. This suggests that at least for the pre-pandemic period, fixed costs may have indeed been rising.

Figure 39: SG&A expenses as a share of turnover have increased steadily before falling around the time of the Covid-19 pandemic

SG&A share in turnover as a proxy for fixed costs shares, using data from Bureau van Dijk's FAME, UK, 2005 – 2021



SG&A expenses = gross profit minus earnings before interest, taxes, depreciation, and amortization (EBITDA). SG&A share in turnover is computed by dividing SG&A expenses by turnover. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from *Bureau van Dijk's FAME* (2005-2021)

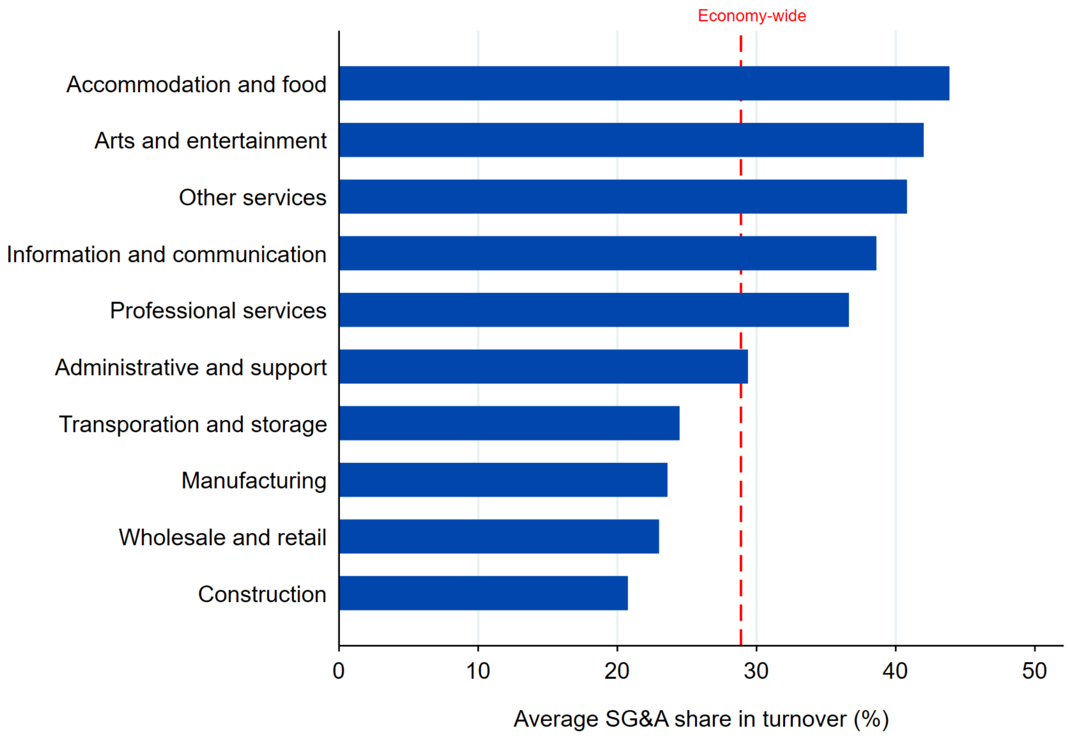
6.37 Future years of annual account returns will allow us to understand to what extent this drop is permanent or a pandemic-related deviation from the long-term trend, perhaps because firms cut back on investment more generally amid widespread economic uncertainty.

6.38 Figure 40 shows the variation in SG&A expenses across sectors. SG&A expenses are generally higher in services than in production, so a deindustrialising economy can expect SG&A costs shares to rise in aggregate. Accommodation and food services have the highest SG&A share in the economy, while construction has the lowest.

6.39 Figure E.30 in the appendix shows how these shares have changed over time. Across sectors, mining and quarrying, transportation and storage and administrative services have seen the largest rise.

Figure 40: Fixed cost shares are generally higher in services industries

SG&A share in turnover as a proxy for fixed costs shares by sector, using data from FAME 2005 – 2021



Average SG&A share in turnover from 2005 to 2021. SG&A = gross profit minus earnings before interest, taxes, depreciation and amortization (EBITDA). SG&A share in turnover is computed by dividing SG&A expenses by turnover. Industries are ranked by largest average SG&A share. Data from *Bureau Van Dijk's FAME* (2005-2021).

6.40 Another way to understand the changing role of fixed costs is to estimate returns to scale. Returns to scale measure how much output changes in response to changes to all inputs simultaneously and therefore helps us understand if technology pushes firms to be larger or smaller.

6.41 If increasing all inputs more than proportionally increases output, returns to scale are increasing; if increasing all inputs less than proportionally increases output, returns to scale are decreasing. If output scales one to one with input increases, returns to scale are constant.

6.42 We can also think about returns to scale from the cost side as the ratio of average costs to marginal costs. Higher returns to scale indicate either that average costs have risen (perhaps due to rising fixed costs) or that marginal costs have fallen (Kariel and Savagar, 2024).

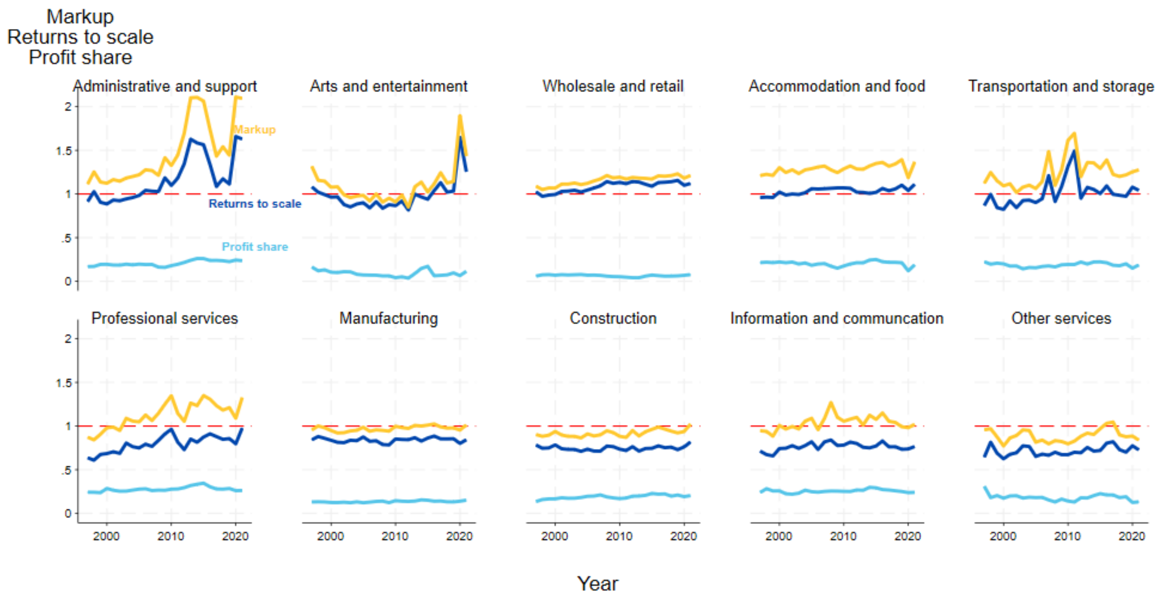
6.43 Because markups can be used to either cover fixed costs or to pay out profits to owners, there is a natural relationship between returns to scale (which depend on fixed costs), markups and the profit rate. Formally, we can estimate returns to scale as equal to the markup multiplied by one minus the profit share. When returns to scale do not change, a rise in markups will be associated with rising profit shares. However, rising returns to scale can break the link between markups and profits.

6.44 We combine our markup estimates at the annual two-digit SIC industry level with estimates of the profit share from the ONS (Black, 2023), and aggregate them to the sector level using turnover shares. Figure 41 plots returns to scale over time alongside markups and profit shares. The dotted red line represents constant returns to scale: the standard benchmark, where a doubling of all inputs leads to exactly a doubling of output.

6.45 The correlation between markups and returns to scale is high; there is significantly less variation in profit shares over time. Therefore, the rise in markups is mostly associated with rising returns to scale, not rising profit shares.

Figure 41: Returns to scale have increased in line with markups, while profit shares have not

Returns to scale estimates across sectors, using baseline estimated markups and Office of National Statistics (ONS) profit shares, 1997 – 2021



Markup computed following the baseline approach in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997 - 2020) and *Annual Business Survey* (2021). Profit shares from the *Office of National Statistics (ONS)* at the annual 2-digit Standard Industrial Classification (SIC) level. Markups and profit shares combined to compute returns to scale, weighted by sales share to aggregate up to the sector level. Industries are ranked by highest returns to scale in 2021. Dotted red line at one for reference.

Technological changes may in turn affect competition

6.46 This section finds some evidence of technological explanations behind the rise in markups. This however need not mean the rise in markups is entirely benign. De Ridder (2024) shows, in the context of an endogenous growth model, that increasing intangible capital inputs can simultaneously lead to a slowdown of productivity growth, a decline in business dynamism, and a rise of market power.

6.47 By reducing marginal costs and increasing fixed costs, intangibles give firms a competitive advantage as well as creating a barrier to entry. Based on a calibration to French and US data, the model predicts that a fall in the cost of intangibles for some firms spurs an initial jump in productivity followed by a decline in productivity growth, consistent with the empirical trends observed since the mid-1990s.

6.48 The initial fast rise in high-intangible firms leads to productivity growth but causes a decline in entry and discourages investment by low-intangible incumbents, causing productivity growth to slow down in the longer term.

6.49 Weiss (2020) studies the effect of a change in technology that increases the output elasticity of intangible capital while reducing the elasticity of standard capital. In this model, a shift toward intangible capital in line with empirical estimates explains more than half the increases in concentration and markups from 1997 to 2012.

6.50 Large productive firms with high markups disproportionately increase investment and gain market shares. Despite an increase in concentration and markups, the model yields a small permanent increase in welfare.

6.51 Chiavari and Goraya (2024) similarly estimate a model with intangible capital as an input and find evidence of technological change biased towards intangible capital. The output elasticity of intangible capital according to this study has tripled in the US since the 1980s while other output elasticities have declined. Because intangible capital investment entails higher adjustment costs than standard capital, the increasing importance of intangibles can explain the observed increase in average firm size, sales-weighted profit rates and industry concentration.

6.52 Eeckhout and Veldkamp (2024) examine the relationship between markups and data, one type of intangible capital. Data facilitates prediction, and thus allows firms to orient supply towards more profitable goods. It also allows firms to reduce risk. Data-rich firms can produce more, which drives prices down. Overall, the model predicts that firms with more data are larger and have higher markups than other firms, but the effect on average markups of the total amount of data and its distribution across firms is ambiguous.

6.53 Aghion, Bergeaud, Boppart, Klenow, Li (2022) analyse a model where falling overhead costs favour big firms. This change encourages highly efficient firms to expand into more markets. After generating a temporary surge in aggregate productivity growth, high-efficiency firms eventually start to discourage innovation and stifle growth. As high process-efficiency firms achieve higher markups on average across the markets in which they operate, they push up the aggregate markup.

6.54 De Loecker, Eeckhout and Mongey (2021) build a model that explicitly sets up a horserace between a technological explanation of markups and changes in market structure. For the US, they find that both types of changes are necessary to replicate trends in markups, labour reallocation and costs between 1980 and 2016. They estimate that these changes have led to a 9% decrease in welfare between 1980 and 2016. Accommodating these two simultaneous changes allows the authors to match patterns of declining business dynamism, declining equilibrium wages and labour force participation, as well as the reallocation of sales towards larger and more productive firms.

6.55 Finally, Gutiérrez, Jones and Philippon (2020) argue that changes to entry costs explain simultaneous trends such as increased corporate profits and concentration, decreased business dynamism and low business investment. These changes raise markups but reduce aggregate demand and investment. A model estimation based on US data confirms that entry costs have risen over the last two decades. Absent entry cost shocks, the authors estimate that labour income, capital and consumption would have been 4-5% higher.

6.56 Overall, our findings of some evidence of continued technological change over the past two decades in the UK is consistent with research elsewhere. At the macroeconomic level, the UK has continued to shift out of manufacturing and into services. In addition, production has become less sensitive to material inputs and the fixed cost share has increased.

M&A activity has risen, but not in the industries with markup rises

6.57 The "pricing power" explanation of markups proposes that incumbent firms have used their position to entrench their power and deter or acquire potential competitors.

6.58 A key channel to understand the relative importance of this explanation is therefore merger and acquisition (M&A) activity. In contrast to other actions firms might take to consolidate their market position, M&A activity is observable in a comparable way across the whole economy.

6.59 This section shows that while the number of mergers has increased over the past decade in the UK, mergers are not concentrated in industries that have seen the largest increases in markups. We show that the use of CMA enforcement tools has been broadly steady. While markups at acquiring firms rise after M&A activity, effect sizes vary considerably across industries.

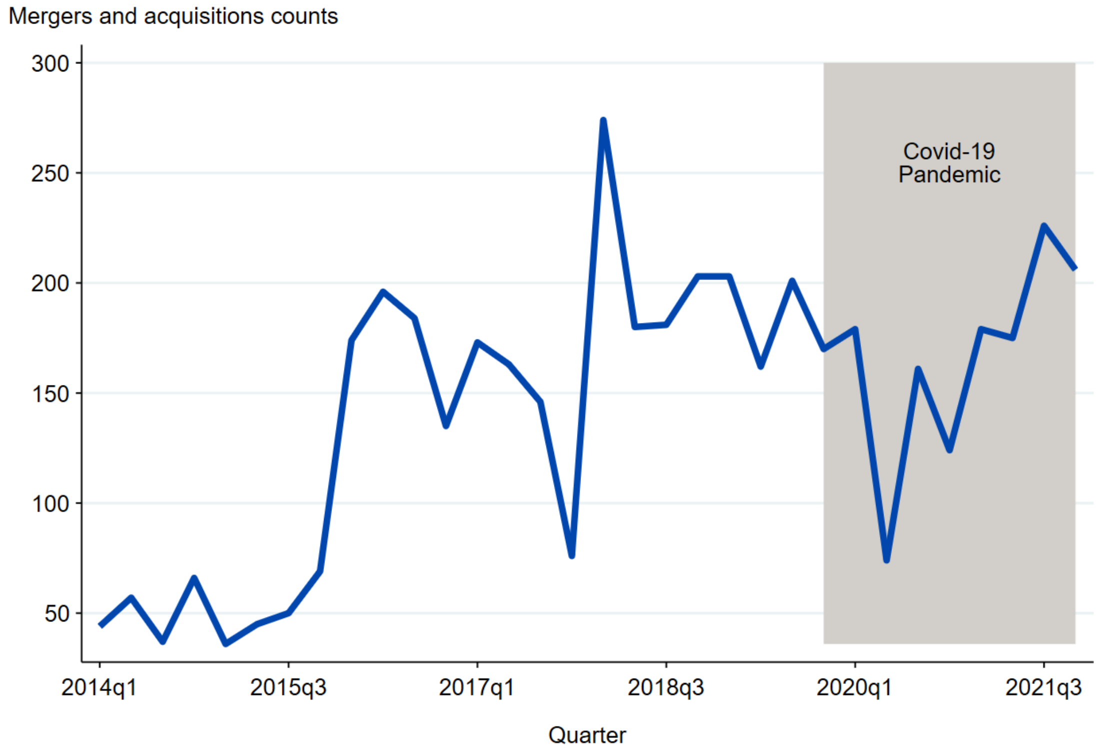
6.60 Figure 42 shows the quarterly number of domestic mergers (that is, transactions where both the acquirer and the target are registered in the UK) with a transaction value of over £1,000,000 from the ONS Mergers and Acquisitions Survey. This of course only captures a very partial picture of M&A activity: many mergers feature international companies or fall below this transaction threshold.

6.61 Therefore, these figures may underestimate the level of M&A activity. For comparison, according to the CMA Annual Report (CMA, 2024), approximately 50,000 M&A deals were identified over the course of 2023. Out of these, the CMA considered 913 merger cases between 2023 to 2024. In the preceding two years, the CMA considered around 700 and 800 mergers respectively.

6.62 Nonetheless, if the rise in markups is driven to a large degree by mergers, we would expect to see some evidence of that relationship in the publicly available merger counts.

Figure 42: Total mergers and acquisitions have risen over the past decade

Counts of UK domestic mergers and acquisitions, data from the Mergers and Acquisitions Survey, 2014 Q1 – 2021 Q4



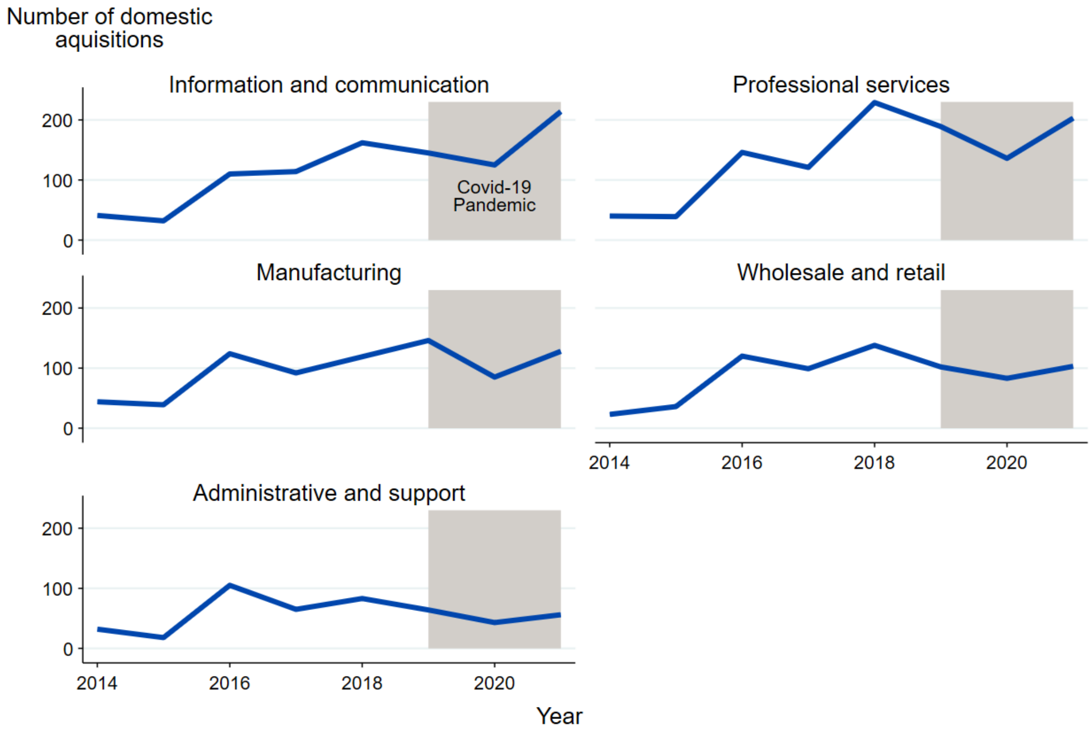
Quarterly counts of UK mergers and acquisitions. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Mergers and Acquisitions Survey* (2014 Q1-2021 Q4)

6.63 Quarterly counts of mergers in the ONS data have risen from 50 in 2014 to a peak of around 275 in 2018. After a fall during the pandemic, quarterly mergers above the transaction threshold now average around 200.

6.64 Across sectors, the number of mergers has remained broadly constant over time in administrative and support services but has risen significantly in information and communication, professional services, and to a lesser degree in manufacturing and wholesale and retail. This can be seen in Figure 43.

Figure 43: Merger numbers have increased significantly in information and communication and in professional services

The number of UK domestic acquisitions by Standard Industrial Classification (SIC) industry, data from Mergers and Acquisitions Survey, 2014-2021



Number of domestic acquisitions by Standard Industrial Classification (SIC) industry. Industries ranked by higest number of domestic aquisitions in 2021. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. SIC sectors F, H, I, R and S are also excluded because of too few observations. Data from the *Mergers and Acquisitions survey* (2014-2021).

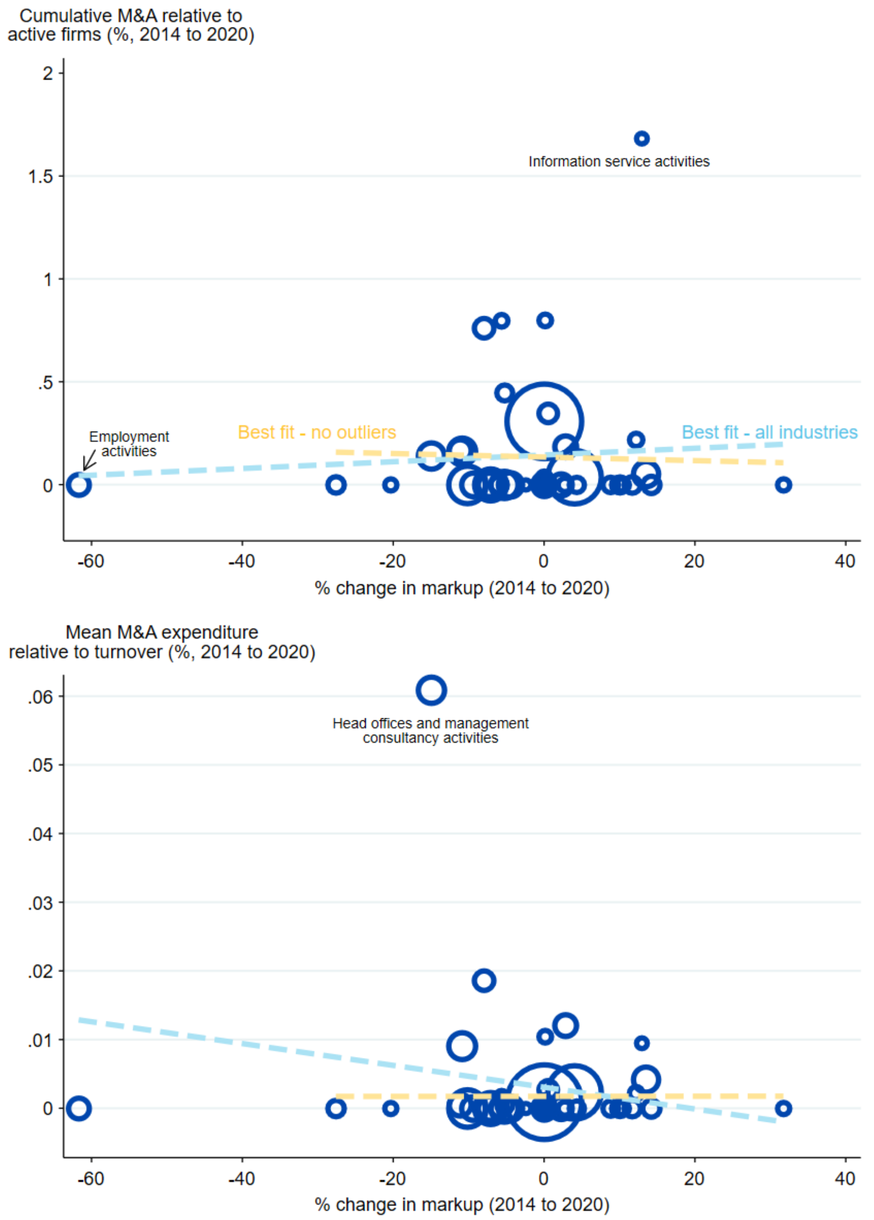
6.65 Panel 1 of Figure 44 plots the cumulative number of M&A deals relative to the size of the industry against the change in industry-level average markup since 2014 (the earliest year the survey data is available).

6.66 If consolidation through M&A activity were a major determinant of increased market power, we would expect the two to be positively related at the industry level. The relative number of M&A deals is only weakly related to the change in markups over this period, driven by a small number of outliers.

6.67 Of course, it could be the case that the number of deals is misleading: perhaps only large deals are able to reshape an industry sufficiently. Panel 2 therefore plots the same change in the aggregate markup against the mean value of the deal in the same industry, over the same period. Again, there is no clear relationship between these two variables.

Figure 44: There is no strong relationship between mergers and acquisitions (M&A) activity and changes in aggregate markups

Panel 1: Scatterplot of the percentage change in markups and cumulative number of mergers and acquisitions as a percentage of average number of active firms by two-digit Standard Industrial Classification (SIC) between 2014 and 2020
Panel 2: Scatterplot of the percentage change in markup and mean mergers and acquisitions expenditure as a percentage of turnover by two-digit SIC between 2014 and 2020
Data from the Annual Respondents Database X (1997-2020), the Annual Business Survey (2021), Business Structural Database (2014-2020), and ONS Merger and Acquisitions Surveys (2014-2020)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents sectoral average turnover. Lines of best fit weighted by average turnover, not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and the 2-digit industries that do not have data for the entire period. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), the *Business Structure Database* (1997-2022) and the *ONS Merger and Acquisitions Survey* (2014-2020).

6.68 Finally, the M&A survey only records transactions above £1,000,000. Smaller acquisitions may still be responsible for the rise in markups.

6.69 Policymakers have recently been concerned about the rise of roll-up acquisitions (that is, sequential acquisitions of several competitors within the same local market), especially by private equity firms (US Federal Trade Commission, 2024). Recently, in its decision to open a market investigation in the veterinary services market, the CMA raised the issue of roll-up acquisitions in this sector (CMA, 2024). The CMA found that between 2013 and 2023, the share of veterinary practices owned by large corporate brands had increased from around 10% to almost 60%.

6.70 Since most roll-up acquisitions likely fall below the ONS reporting threshold, the ONS quarterly domestic merger counts may be misleading.

6.71 Figure 45 therefore plots the change in markups against the cumulative number of establishments that have changed owner on the UK business register, by two-digit SIC industry. This wider measure of M&A activity allows us to capture M&A activity below the threshold, at the cost of wrongly including some administrative changes that are not true ownership changes.

6.72 As Figure 45 shows, there is also no strong relationship between industry-wide markups and this wider measure of M&A activity.

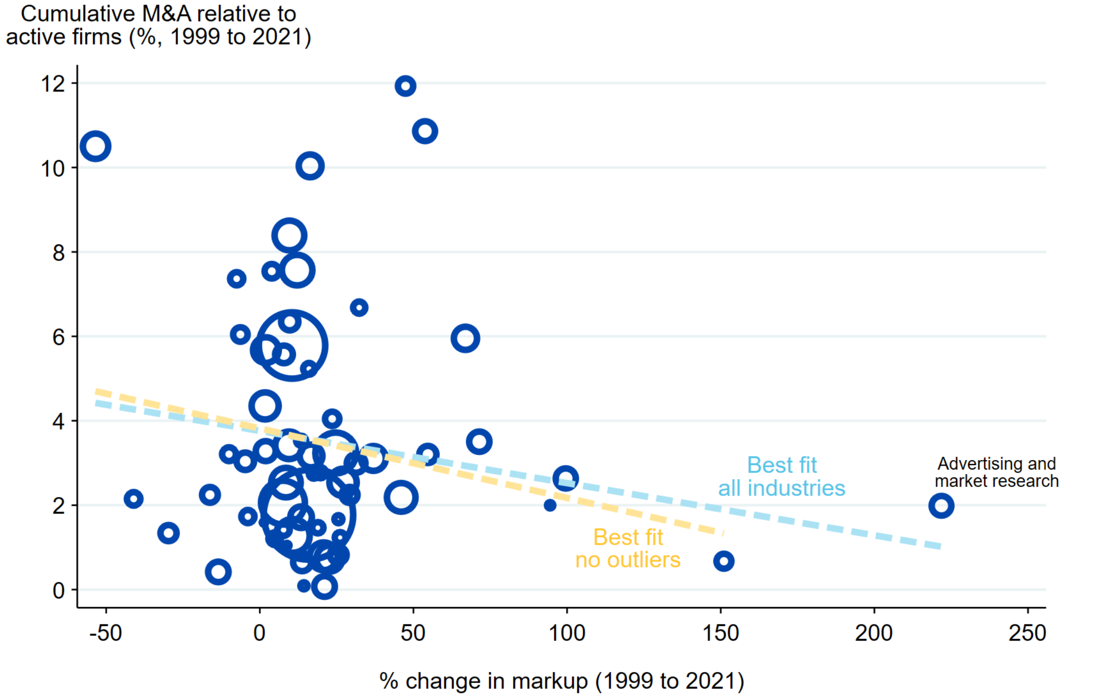
6.73 For the US, Levonyan and Mengano (2024) examine the extent to which M&A activity can explain the observed trend of rising market power. They find that mergers account for 40% of the overall rise in US markups. More than half of this 40% merger-driven markup rise is in turn explained by revenue transfers between merging firms, from lower-markup to higher-markup firms. This stands in contrast to our UK findings in this report.

6.74 Related to the observed increase in US M&A activity, Lancieri, Posner and Zingales (2023) argue that US competition enforcement has become less stringent in recent decades, and that this change is at least partly to blame for the rise in US mergers and consequently markups.

6.75 Comparing the level of enforcement across countries with differing legal systems is inherently difficult. For instance, UK merger inquiries do not go through the court system in the same way as US merger inquiries.

Figure 45: There is no strong relationship between mergers and acquisition (M&A) activity and changes in aggregate markups

Scatterplot of percentage changes in markups and cumulative M&A (local units to enterprises) as a percentage of average active firms between 1999 and 2021 at a two-digit Standard Industrial Classification (SIC) level, from the Annual Respondents Database x (1997-2020), the Annual Business Survey (2021) and the Longitudinal Business Database (1997-2021)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents sectoral average turnover. Lines of best fit weighted by average turnover, not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and the 2-digit industries that do not have data for the entire period. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), and the *Longitudinal Business Database* (1997-2021).

6.76 The CMA has several tools to combat excessive market power. It can investigate mergers and acquisitions (through shorter “Phase 1” and more in-depth “Phase 2” investigations). Where mergers lead to a substantial lessening of competition, the CMA can block them or prescribe remedies to the merging firms.

6.77 The CMA also has the power to investigate antitrust cases (such as price or wage fixing) and may review competition in an entire market using the market study and market investigation tools.

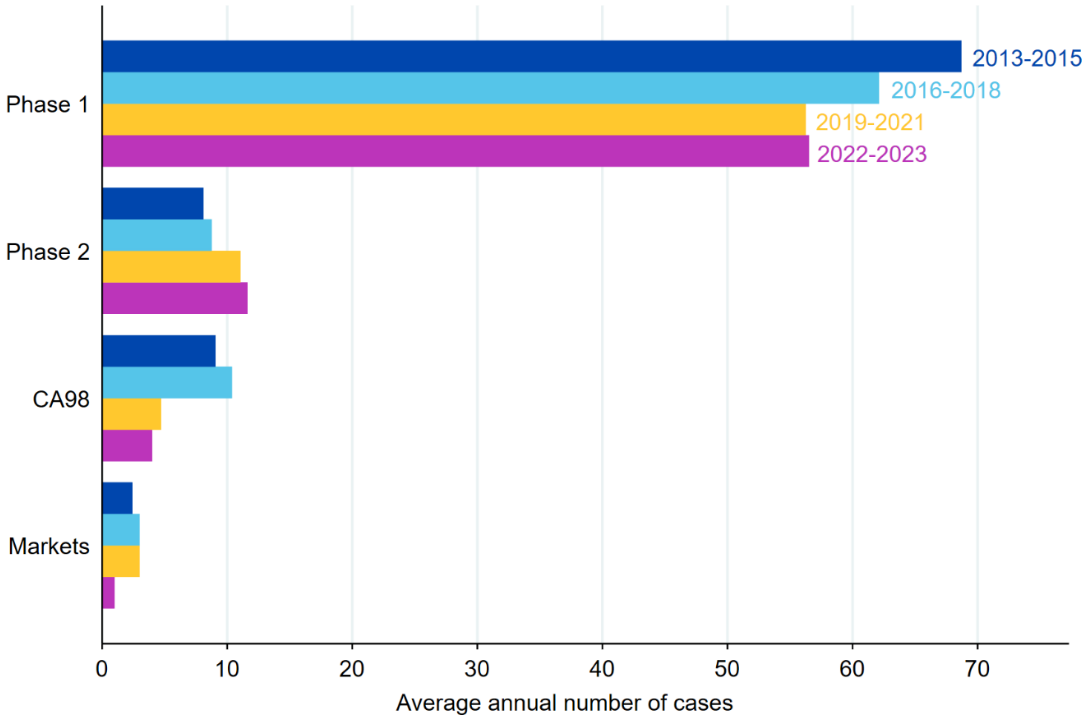
6.78 This section shows that the number of merger and antitrust cases (CMA tools for which data is available) has been roughly steady over the last ten years.

6.79 Figure 46 plots average counts of competition cases across four major CMA tools for which we have data available. These are Phase 1 and Phase 2 merger investigations, antitrust cases and market studies and investigations. The relative frequency of cases reflects to some extent how time- and resource intensive they are. Phase 1 merger investigations usually last ten weeks, while market studies and antitrust cases can last for many months or even years.

6.80 As Figure 46 shows, the use of all tools is relatively stable across the last decades. Market studies and Phase 2 cases have seen a slight rise, and antitrust investigations a slight decline.

Figure 46: CMA enforcement case numbers have overall been steady over the last decade

Number of mergers phase one, mergers phase two, CA98 investigations, and markets cases over three periods, from Competition and Markets Authority (CMA) internal data. Phase one, phase two and markets cases: annual data 2013-2023. CA98 cases: annual data 2013-2022. Excluding ongoing cases



Annual average number of cases in each sub-period. Tools orderd by highest average in the final period. Cases from *Competition and Markets Authority (CMA) internal data*, 2013-2023. Excluding cases still ongoing. CA98 investigations data only until 2022.

6.81 Overall, case numbers across competition enforcement tools at the CMA have been relatively steady over time. For instance, the number of phase 2 mergers reviewed by the CMA has slightly increased. This stands in contrast to the US experience, where the number of litigated mergers in recent decades has fallen (Lancieri, Posner and Zingales (2023)).

6.82 The number of cases, however, does not provide a full picture of the level of enforcement and can therefore be misleading. For example, Phase 1 mergers in the UK include voluntary filings, which may be less problematic from a competition perspective. The number of Phase 2 cases, which tend to capture potentially more problematic mergers, depends on many factors, including the complexity of the deals that the CMA scrutinises each year.

6.83 Therefore, while these charts provide some context for other results in this report, they are not on their own sufficient to evaluate the activities of the CMA. The annual impact assessment (CMA, 2023) gives a much fuller account of the impact of the CMA's competition enforcement across its various tools.

6.84 Moreover, due to data limitations we are unable to speak to the period between 1997 and 2012, when aggregate markups in the UK have risen the fastest.

6.85 Finally, while it does not appear that mergers are behind the rise in industry-level markups, we can also ask what happens to markups of firms that acquire another firm.

6.86 Figure 47 shows the average change in the acquirer markup in the two years following an acquisition, compared to the two years preceding it. On average, markups rise slightly, but there is significant variation across the economy.

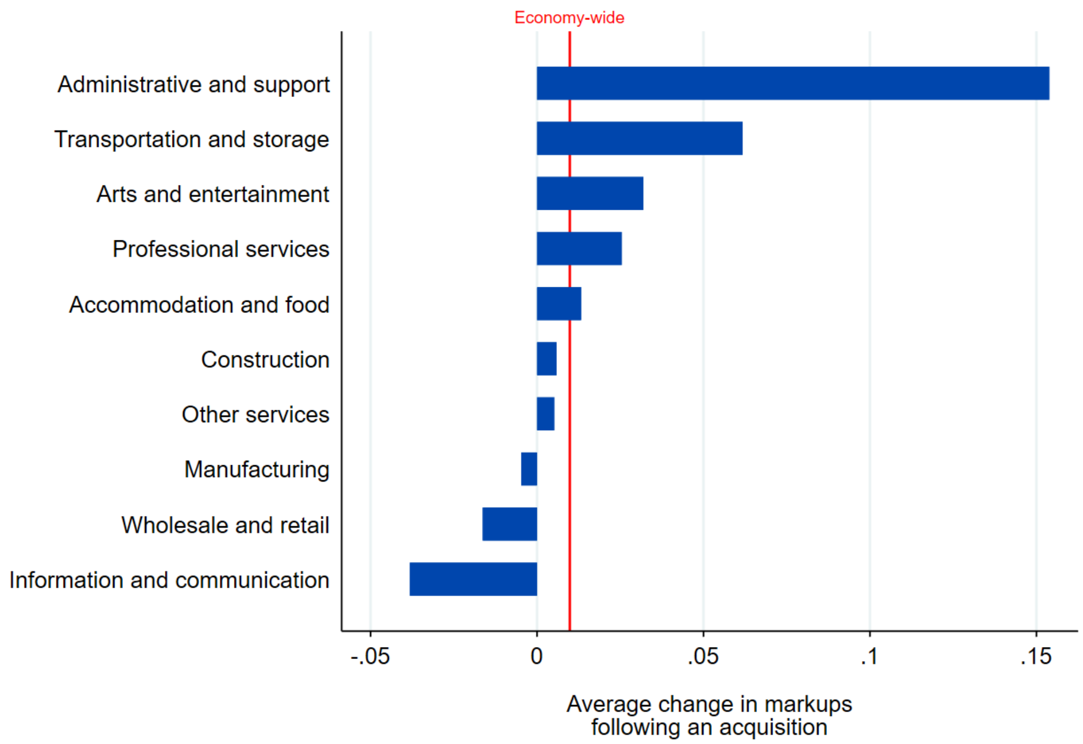
6.87 A more accurate comparison would compare this rise to non-acquiring companies with similar characteristics and markup trends. Therefore, this figure should not be taken as illustrating the effect of acquisitions on markups of the acquirer. A more like-for-like comparison lies outside the scope of this report, but we hope to revisit this in future work.

6.88 Similarly, an increase in acquirer markups would be expected under both a market power explanation and an efficiency explanation of mergers. Therefore, more work is needed to disentangle the two.

6.89 Overall, this section has presented the available evidence for the technology and market power explanations of rising markups. Since 1997, the UK has continued to shift out of manufacturing and into services. This will affect the average markup. Even within industries, production technologies have become less sensitive to material inputs and more sensitive to labour. Firms spend more on fixed costs, and returns to scale have increased in services.

Figure 47: On average markups increase by about 1% following an acquisition but this varies significantly between broad industries

Average change in markups following an acquisition at the economy level and broken down by sector. This is calculated by taking the difference between the average markup for the two years before and two years after the acquisition. Data from the Annual Respondents Database X (1997-2020), the Annual Business Database (2021) and the Longitudinal Business Database (1997-2021)



Estimates are the average change in markups following an acquisition. Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X*(1997-2020), the *Annual Business Survey* (2021) and the *Longitudinal Business Database* (1997-2021).

6.90 At the same time, the number of mergers has increased, particularly in services. Neither the number nor the value of mergers can account for industry differences in the rise of markups though. While US evidence shows falling competition case numbers, the use of CMA tools over the past decade has remained constant. While case numbers are a very crude measure of enforcement, we do not find evidence that rising consolidation or weakening competition enforcement are the main driver of rising cost markups.

6.91 Overall, these new findings point towards a mixed story, with technological changes explaining at least some of the rise in aggregate markups.

7 Market power and economic outcomes

7.1 Firms might be able to charge high markups for benign or less benign reasons. Perhaps they are innovating, producing new products and services consumers want. Perhaps they can produce or market existing products at lower cost. Alternatively, they may acquire competitors, prevent new entrants from competing and exploit the lack of competition by raising prices or reducing variety.

7.2 The previous chapters have documented that overall markups have risen in the UK, by a similar magnitude as in other European countries, have found that concentration has stayed constant and business dynamism has fallen. The last chapter has assessed the weight of the evidence for technology and market power explanations of the rise in markups.

7.3 This chapter looks at the relationship between markups on the one hand and economic outcomes like investment, innovation, productivity, and price changes on the other. An understanding of how markups are related to consumer outcomes and drivers of economic growth allows policymakers to put changes to competition across the economy in the context of other macroeconomic policy priorities.

7.4 We find that at the industry level, markups appear unrelated to investment, innovation, productivity, and price increases. At the firm level, higher productivity is followed by increasing markups, but not the other way around. This suggests that productivity increases allow firms to increase their markups.

7.5 The lack of a strong relationship with investment, innovation, productivity, and inflation suggests that changes in market power are unlikely to be the major contributors to the UK's recent policy challenges, such as low business investment rates. Changes in market power are also unlikely to explain the UK's uniquely low productivity growth relative to peer economies given similar international markup trends.

7.6 We show that the dispersion of markups in the UK has increased over time. This may indicate that the distortions due to market power in the aggregate have worsened over the last two decades.

7.7 Finally, we use a simple machine-learning algorithm to cluster industries into groups based on the various measures of competition employed throughout the report. This highlights the importance of a comprehensive assessment to understand competition in an industry but can also act as a diagnostic tool for policymakers.

7.8 Policymakers can use the tool to understand industry differences and dynamics more comprehensively, for instance by looking at markup changes in the context of entry and exit rates, productivity growth or price changes.

7.9 We find that several industry clusters with high markups nonetheless feature high productivity, investment, and business dynamism. However, we also identify a cluster of four service industries with the highest markups and low or falling job reallocation, firm entry and exit rates. This cluster may merit further investigation.

Market power and investment, innovation, and productivity

7.10 This section reports industry-level relationships between markups and outcomes of interest. Industry-level relationships can of course mask many important details. For instance, an industry with a single, large quasi-monopolist and a competitive fringe of small firms may behave quite differently from one with equally sized, oligopolistic competitors, even if average markups are the same.

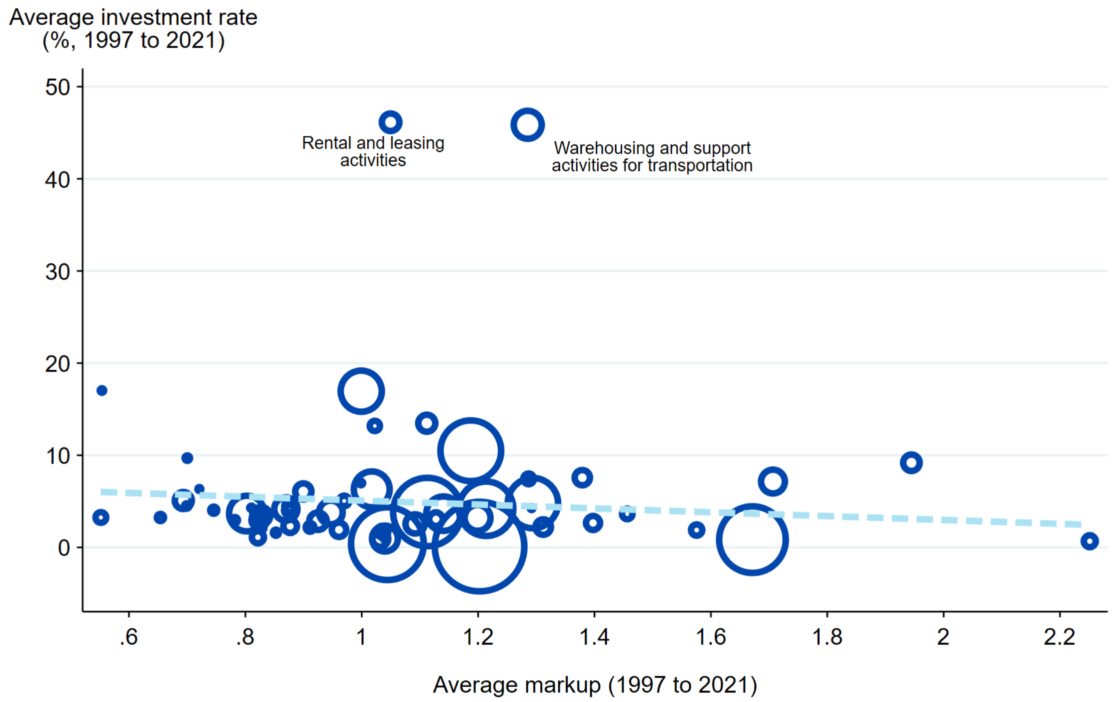
7.11 By lowering demand, higher markups may depress the demand for capital inputs, potentially lowering the investment rate, the price of capital and the capital share. De Loecker, Eeckhout and Unger (2020) find a small decline in the capital share in the US since the 1980s, while Gutiérrez and Philippon (2017) argue low US business investment is linked to rising market power.

7.12 Conversely, higher markups could increase innovation, because firms may compete more intensely to replace incumbents in profitable markets, in turn leading to stronger productivity growth. This is in line with arguments made by Aghion, Bloom, Blundell, Griffith and Howitt (2005).

7.13 Figure 48 shows the relationship, at the two-digit industry level, between the average investment rate and the average markup. Investment rates across industries are uncorrelated with markup levels. This suggests that market power is unlikely a major driver of the UK’s flagging business investment rate in recent decades.

Figure 48: There is no correlation between the relative amount of investment and the average markup at sector level

Scatterplot of investment as a percentage of turnover against markups at sector – year level, data from Annual Respondents Database X, Annual Business Survey, and ONS Business Investment by Industry and Asset data, 1997 - 2021



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fits weighted by turnover, not statistically significant at the 5% level (as represented by the dashed line). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U and 2-digit industries that we do not have data for in every single year. Investment rate calculated by dividing investment by turnover. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020) and the *Annual Business Survey* (2021).

7.14 Industries with different levels of markups may behave differently when it comes to innovation. On the one hand, larger markups may indicate that competition is not particularly fierce, and therefore firms may see less need to innovate. On the other hand, high markups may create incentives for new firms to innovate in an attempt to capture the market or may be the result of past successful innovation.

7.15 Ideally, we would look at innovation outcomes, but these are often difficult to observe, as innovation activities are risky and often pay off with a lag of many years, if at all. Therefore, we focus on the link between markups and innovation inputs, particularly how much firms spend on innovation.

7.16 Additionally, due to data constraints we are only able to look at one specific type of innovation: formal research and development (R&D). There are two ways we can measure R&D: the decision to engage in R&D at all (what economists call the "extensive margin") and the amount of spending for those firms that engage in R&D (what economists call the "intensive margin").

7.17 Panel 1 of Figure 49 below shows the extensive margin of R&D plotted against markups at the two-digit industry level. On average, the share of firms engaged in R&D is not strongly related to the level of markups.

7.18 However, caution is needed for three reasons: first, formal R&D is only one part of wider innovation activities. Second, R&D measures capture inputs into the innovation process, but not innovation outcomes (like patents, or successful product introductions). Third, Panel 1 of Figure 49 only considers the extensive margin (the decision whether to do R&D at all) and not the intensive margin (how much R&D to do).

7.19 Panel 2 of Figure 49 therefore instead shows the intensive margin of R&D against markups at the sector level. The share of R&D spending at the sector level also seems to be unrelated to the level of markups. This suggests neither of the two stories commonly discussed in policy circles (that size and market power is necessary for firms to innovate, and that a slowdown in competition is in part to blame for low investment rates) is obviously supported by the available industry-level data.

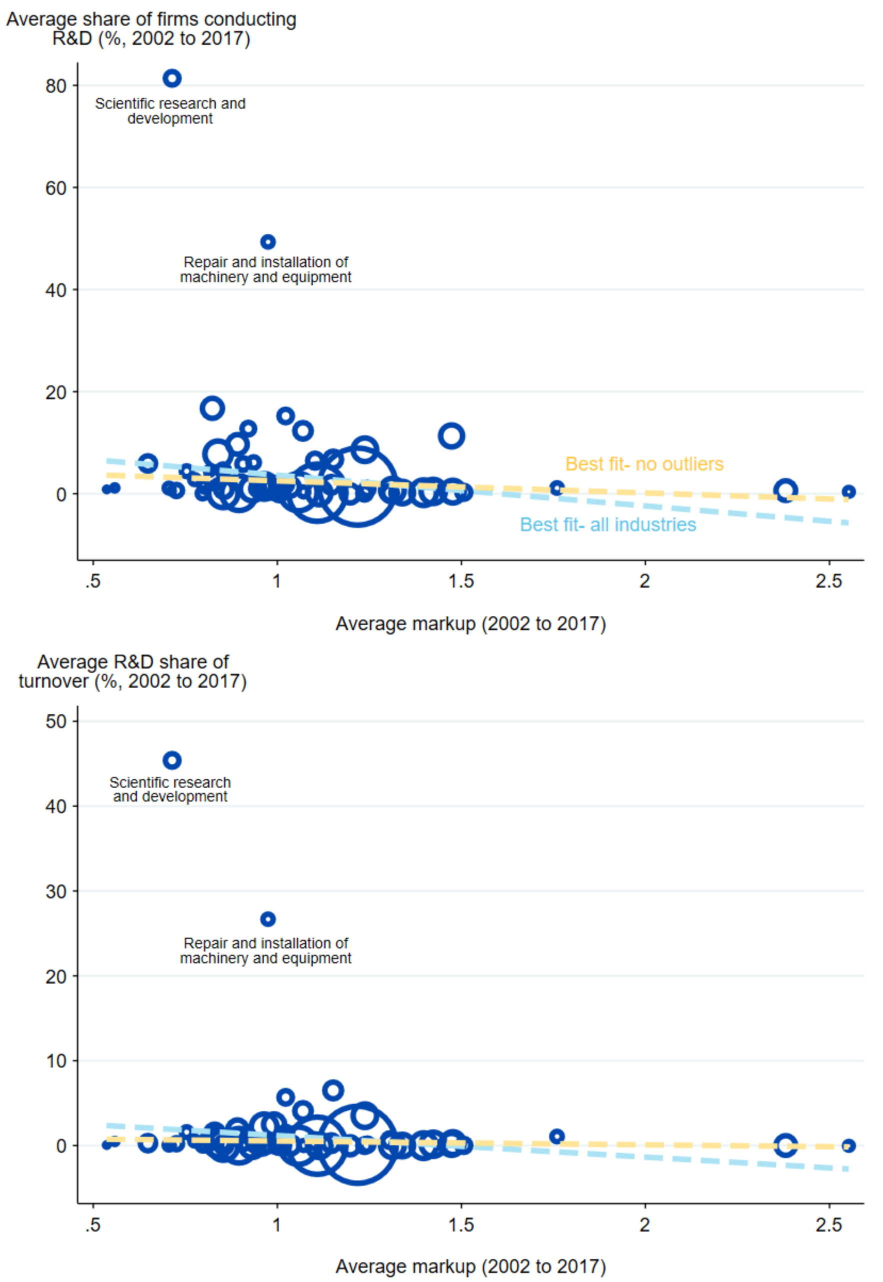
7.20 Productivity captures how efficiently firms convert inputs into output. Efficiently converting inputs into outputs gives firms a cost advantage. Likewise, producing an output of higher quality with the same inputs would be captured by higher productivity.

7.21 In the short run, both cost advantages and higher quality may allow firms to increase their markups. This creates an incentive for firms to improve their productivity. If markets function well, other firms will innovate too in order to capture these profits, driving markups back down towards zero. This process plays out continuously across the economy.

7.22 We would therefore perhaps expect that productivity and markups are positively related. This is indeed the case across firms within industries, but not across industries, where other technological factors also matter.

Figure 49: The share of active firms that are known to conduct R&D and markups are not strongly correlated

Panel 1: Scatterplot of the share of active firms that are known R&D conductors and markups at the two-digit Standard Industrial Classification level, from the Business Enterprise Research and Development survey (2002-2017), the Annual Respondents Database x (2002-2017) and the Business Structure Database (2002 to 2017)
Panel 2: Scatterplot of average R&D expenditure share of turnover against average markups between 2002 to 2017, data from Annual Respondents Database X, Annual Business Survey, and Business Enterprise Research and Development Survey



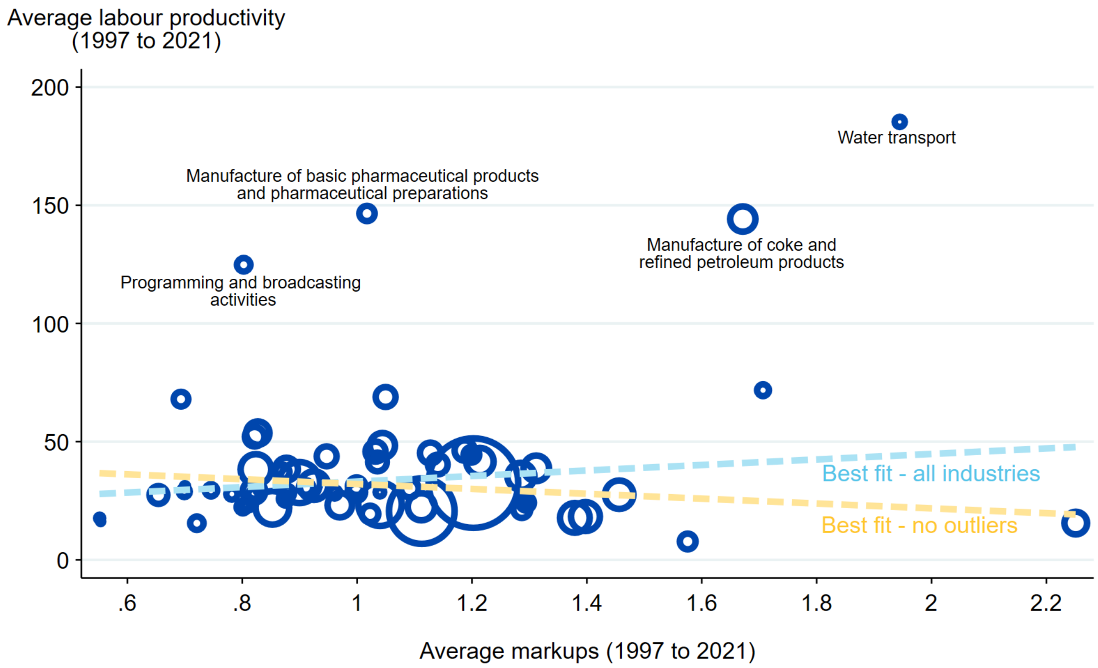
Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fits weighted by turnover, not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U. Markups estimated using our baseline approach described in the report. Sources: the *Business Enterprise Research and Development survey* (2002-2017), the *Annual Respondents Database X* (2002-2017), and the *Business Structure Database* (2002-2017).

7.23 Figure 50 plots the relationship between productivity and markups at the two-digit industry level. Markups and productivity appear slightly positively correlated, but the relationship is neither particularly strong nor statistically significant.

7.24 At the firm level within industry, a similar picture emerges. When we look at the relationship between productivity and markups within the same firm and controlling flexibly for time trends and firm characteristics to single out the relationship between productivity changes and markup changes, productivity and markups remain positively and significantly related.

Figure 50: Productivity and markups are uncorrelated at the industry level

Scatterplot of labour productivity against markups at Standard Industrial Classification (SIC) industry level, data from the Annual Respondents Database X, Annual Business Survey and ONS Labour productivity by industry division, 1997-2021



Each data point represents a 2-digit Standard Industrial Classification (SIC) sector, size represents average sectoral turnover. Linear fit weighted by turnover, not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U and 2-digit sectors that we do not have data for in every single year. Labour productivity defined as real output per hour. Markups are calculated following our baseline approach described in the report. Sources: *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), the *Business Structure Database* (1997-2021) and *Office for National Statistics Labour productivity by industry division* (1997-2021).

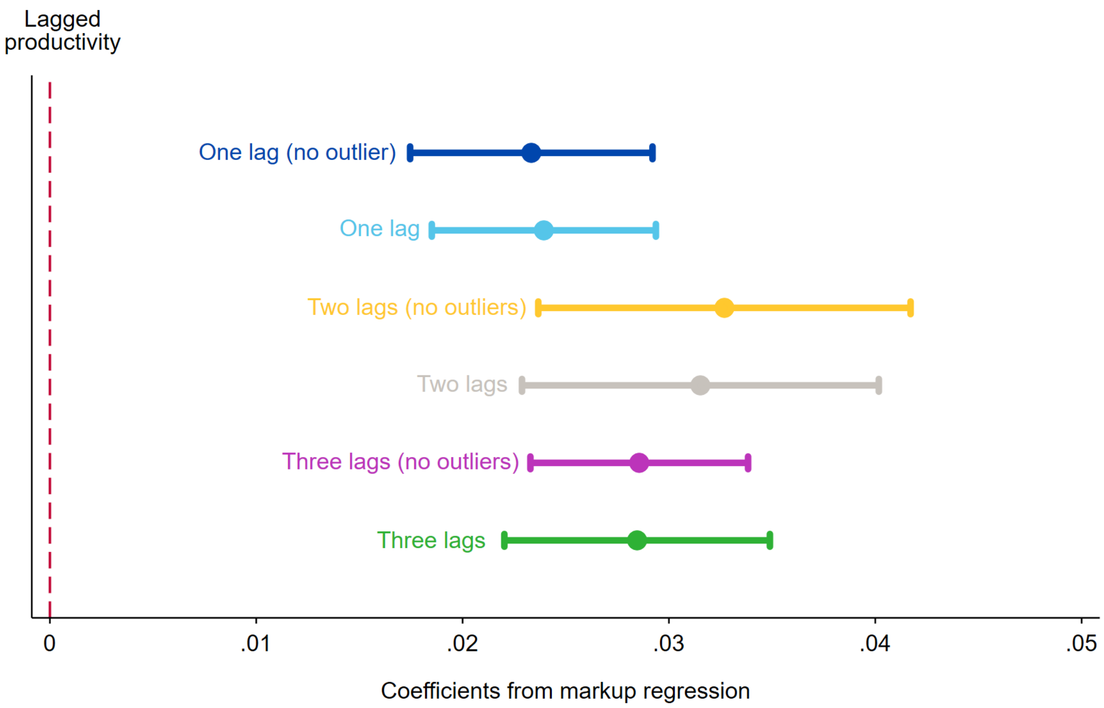
7.25 Figure 51 shows the relationship between productivity in one period and markups in the next, after controlling for firm characteristics. We plot regression coefficients with and without outliers and allowing for more or less persistence in productivity changes.

7.26 Across specifications, the relationship between productivity and markups is positive. When productivity rises, markups the following year rise significantly. This could be because firms are now more efficient at producing their goods and services, or because consumers value it more. Conditional on last year's productivity, productivity in the more distant past does not seem to matter.

7.27 By contrast, Figure E.43 in the appendix shows that current markups are not positively related to future labour productivity at the firm level. This suggests that higher markups are not immediately followed by productivity improvements. If firms are investing the returns from their high markups to improve their productivity advantage further, we do not see this in the regressions.

Figure 51: Markups and the previous year's productivity are positively correlated at the firm level

Coefficient plot of markups against the previous year's labour productivity between 1997 to 2021, data from the Annual Respondents Database X and the Annual Business Survey



The coefficients come from various regression specifications of markups versus lagged labour productivity, defined as sales per worker. Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997-2020) and the *Annual Business Survey* (2021).

Markups are not related to price changes at the industry level

7.28 The relationship between prices and markups is informative in more than one way. First, prices, not markups, affect consumer welfare directly. Second, how prices and markups move together provides another clue as to where the rise in markups is coming from: for instance, firms could be reducing marginal costs, they could be increasing the value of the product, or they could be implementing strategies to lock consumers in. Each of these will increase markups but have different implications for prices and welfare.

7.29 If firms lowered costs, we would see markups rise but prices would stay constant or fall. If firms improved the quality of the good, prices would rise but so would consumer welfare. By contrast, if consumers became less responsive to price (for instance, because searching for alternative products became more difficult), prices would rise, and consumer welfare would fall.

7.30 Brand (2021) finds that US consumers have become significantly less price sensitive between 2006 and 2017, with an average decrease of approximately 25% in own-price elasticities and a similar change in cross-price elasticities. This means that consumers will be less likely to reduce the quantity bought or switch products in response to a price rise.

7.31 Brand attributes this change to an increase in product differentiation. Consumers buy products that better match their own tastes, allowing suppliers to exert more market power within their narrow niche.

7.32 Bornstein (2020) studies the role of consumer inertia as a potential driver of the increase in markups. In other words, perhaps consumers simply do not search enough for better or cheaper products. If younger consumers are more likely to search, population ageing can increase the amount of consumer inertia in the economy.

7.33 This in turn may discourage entry by new firms and decrease competition between existing providers. As a result, large incumbents are able to raise markups and production shifts towards larger, high-markup firms. Bornstein estimates that 30% of the rise in US markups can be explained by a rise in consumer inertia.

7.34 Döpper, MacKay, Miller and Stiebale (2024) estimate a 30% increase in US aggregate consumer product markups between 2006 and 2019. This shift of product-level markups is not confined to only high-markup products and is driven by both a price increase and a cost decrease. The price increase reflects an estimated 30% decline in price sensitivity, likely due to a decline in the average time spent shopping. Since 2012, the rise in US product markups is driven mostly by cost reductions achieved through technical improvements.

7.35 Conlon, Miller, Otgon and Yao (2023) do not find any clear correlation between markup increases and price increases and thus similarly point to marginal cost reductions that are not being passed on to consumers.

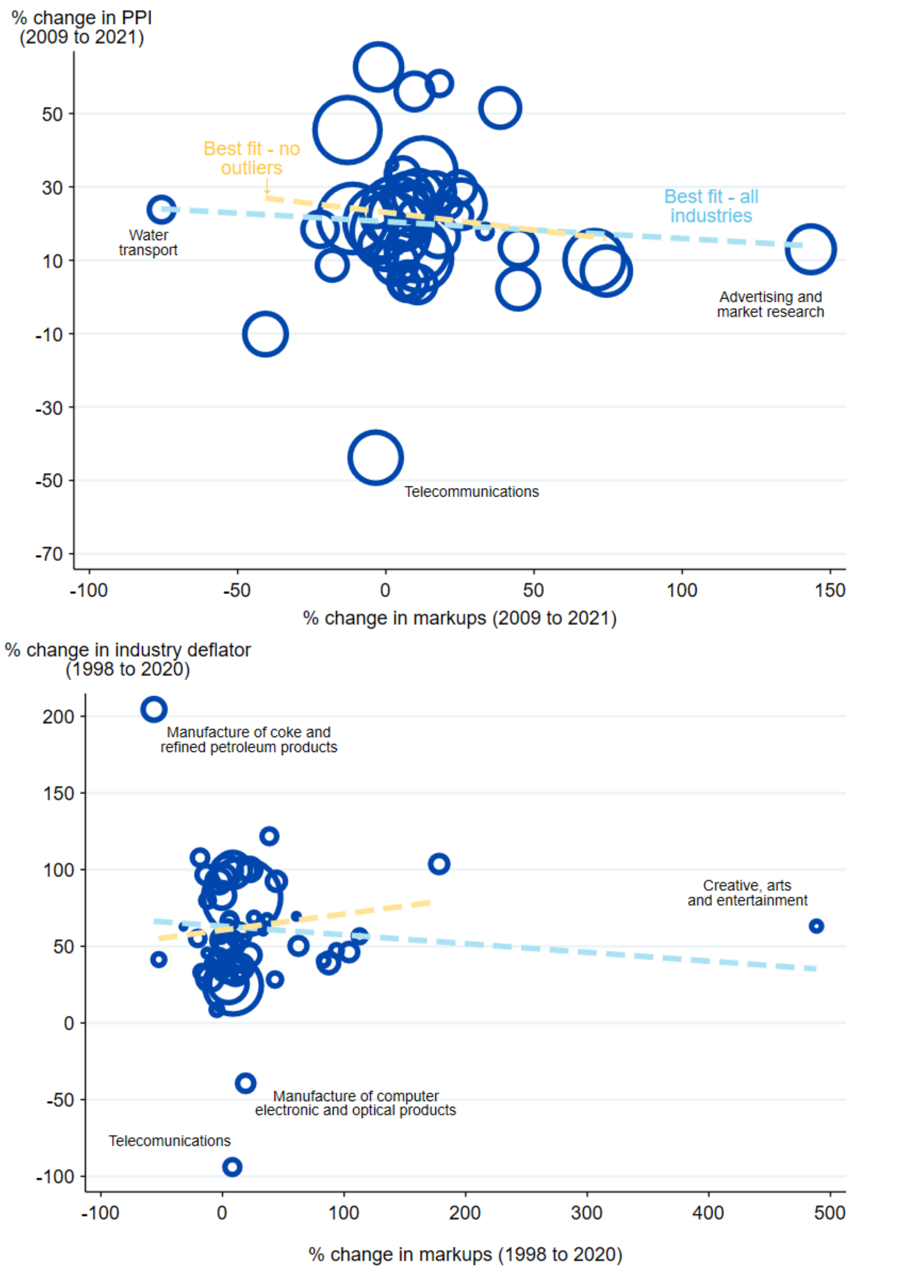
7.36 Figure 52 across two panels shows two different measures of industry-wide price changes plotted against changes in industry-level markups over the same period for Great Britain. Panel 1 uses the Producer Price Index, while panel 2 uses GDP deflators instead.

7.37 Across both panels, industry level price changes are at best weakly correlated with markup changes over the same period. This suggests that in Great Britain too markup changes are unlikely to be the primary driver of price changes.

Figure 52: Price changes are uncorrelated with markups at the industry level

Panel 1: Scatterplot of change in markups and change in Producer Price Indices between 2009 and 2021 by two-digit Standard Industrial Classification (SIC) industry, data from the Annual Respondents Database X, Annual Business Survey, ONS Services Producer Price inflation time series and ONS Producer Price Inflation time series.

Panel 2: Scatterplot of change in markups and change in Industry deflators between 1998 and 2020 by two-digit Standard Industrial Classification (SIC) industry, data from the Annual Respondents Database X, Annual Business Survey and ONS industry deflators and producer and service producer price inflation time series



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents sectoral average turnover. Lines of best fit weighted by average turnover, not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and the 2-digit industries that do not have data for the entire period. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1998-2020), the *Annual Business Survey* (2021), the *Business Structure Database* (1998-2021), the *ONS manufacturing, construction OPI and SPPI for all other sectors* (2009 to 2021), and ONS *Industry Level Deflators (1998 to 2020)*.

Competition and aggregate welfare

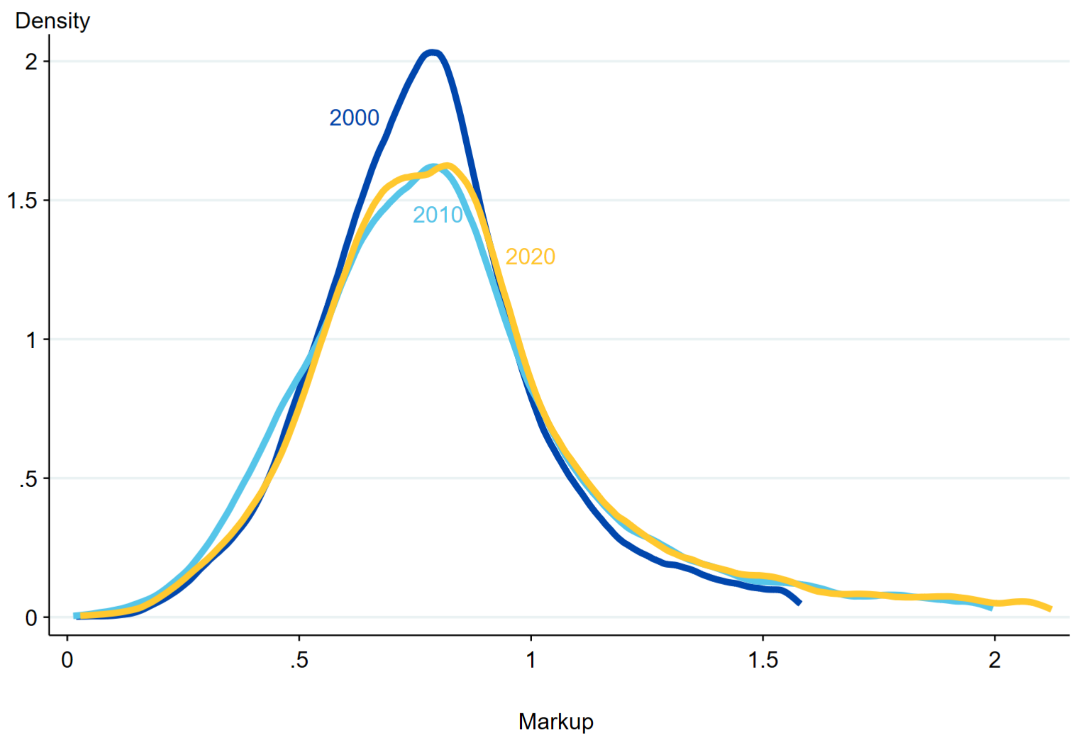
7.38 Without making many more assumptions about how firms compete and how consumers behave, it is impossible to say by how much the rise in markups or the fall in business dynamism have harmed consumers overall.

7.39 However, many researchers think that the dispersion in firm-level productivity or markups may be a good proxy for the level of friction in the overall economy. This is because in a frictionless economy, productivity improvements would quickly spread through the economy, either via learning and diffusion, or because low-productivity firms would exit the market. Therefore, a lack of markup dispersion across the economy is a good measure of the strength of the competitive process.

7.40 Figure 53 shows that markups have become more dispersed in Great Britain since the beginning of the century. Most of this change has taken place between 2000 and 2010. This indicates that the distortions created by market power have likely increased over the past two decades, but less so recently.

Figure 53: Markups in Great Britain have become more dispersed since 2000

Distribution of markups truncated at the 95th percentile for the years 2000, 2010 and 2020. Data from Annual Respondents Database X (ARDx) 1997-2020. GB only



Distribution of markups. Markups estimated using our baseline approach described in the report. Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Data from *Annual Respondents Database X* (1997-2020) and the *Annual Business Survey* (2021).
Note: each distribution has been truncated at the 95 percentile.

7.41 The increase in the dispersion of the markup distribution has increased the distance between the laggard firms and the frontier. Since we know that high-markup firms are generally older and larger, this is another piece of evidence that the UK economy has become less dynamic over the past twenty-five years.

Industry conduct differs systematically across the economy

7.42 This report has outlined how market power in the UK economy has evolved in the last twenty-five years, across multiple dimensions. Across the whole economy, average markups have risen slightly, business dynamism has fallen, and concentration has remained stable. We have related these changes to economic outcomes that policymakers care about, such as price changes, investment, innovation, and productivity.

7.43 Yet individual measures can give an incomplete picture because industries differ systematically in their market structure and competitive conduct.

7.44 In this section, we therefore use a simple k-means machine learning algorithm (Lloyd, 1982) to divide industries into archetypes based on the full spectrum of market power and market structure measures.

7.45 The algorithm takes all the industries and divides them into two, then three, then four (and so on) groups to minimise the unexplained variation in our market power measures within groups. It therefore captures similarities across industries without having to assume anything specific about the nature of competition in these industries.

7.46 We stop increasing the number of groups once adding additional groups no longer significantly increases the share of variation captured by the clusters.

7.47 We cluster industries at the three-digit SIC industry level across all major competition indicators in this report. They fall into four categories: markups, static concentration measures (HHI and CR10), dynamic competition measures (entry, exit, job reallocation and persistence rates) and four relevant industry-level economic outcomes (R&D, investment, productivity, and prices). For each indicator, we consider the 2020 level and the total change between 2005 and 2020.

7.48 Clustering across industries allows policymakers to develop a better understanding of how industry structure and firm conduct differs across industries and potentially identify parts of the economy for more in-depth analysis.

7.49 Figure 54 below shows the outcome of this exercise. To visualise the clusters, Figure 54 plots a heatmap of cluster averages for each of our competition measures (markups, static competition measures, dynamic competition measures, economic outcomes). The clusters are ranked by their average markup, from lowest (left hand side, lightest colour) to highest (right hand side, darkest colour). Across all variables, cell colours in the heatmap show how competitive a cluster is on each measure on average, again ranging from light (most competitive) to dark (least competitive).

7.50 Overall, we find the economy can be divided into twelve clusters of on average fourteen industries, based on the nature of competition in those industries. Individual clusters range in size between one and forty-eight industries. Most clusters include multiple sectors, meaning that sectors are not a good proxy for competitive conduct between industries or indeed for markets.

7.51 The cluster with the highest markups consists of four industries, namely creative arts and entertainment, temporary employment activities, information services and the organisation of conventions and trade shows. In addition to high markups, these industries have also seen the largest increase in markups, and low or declining entry, exit and reallocation rates. Despite this, concentration in these industries is neither particularly high nor increasing, indicating that concentration measures alone are not a good guide to an industry's competitiveness.

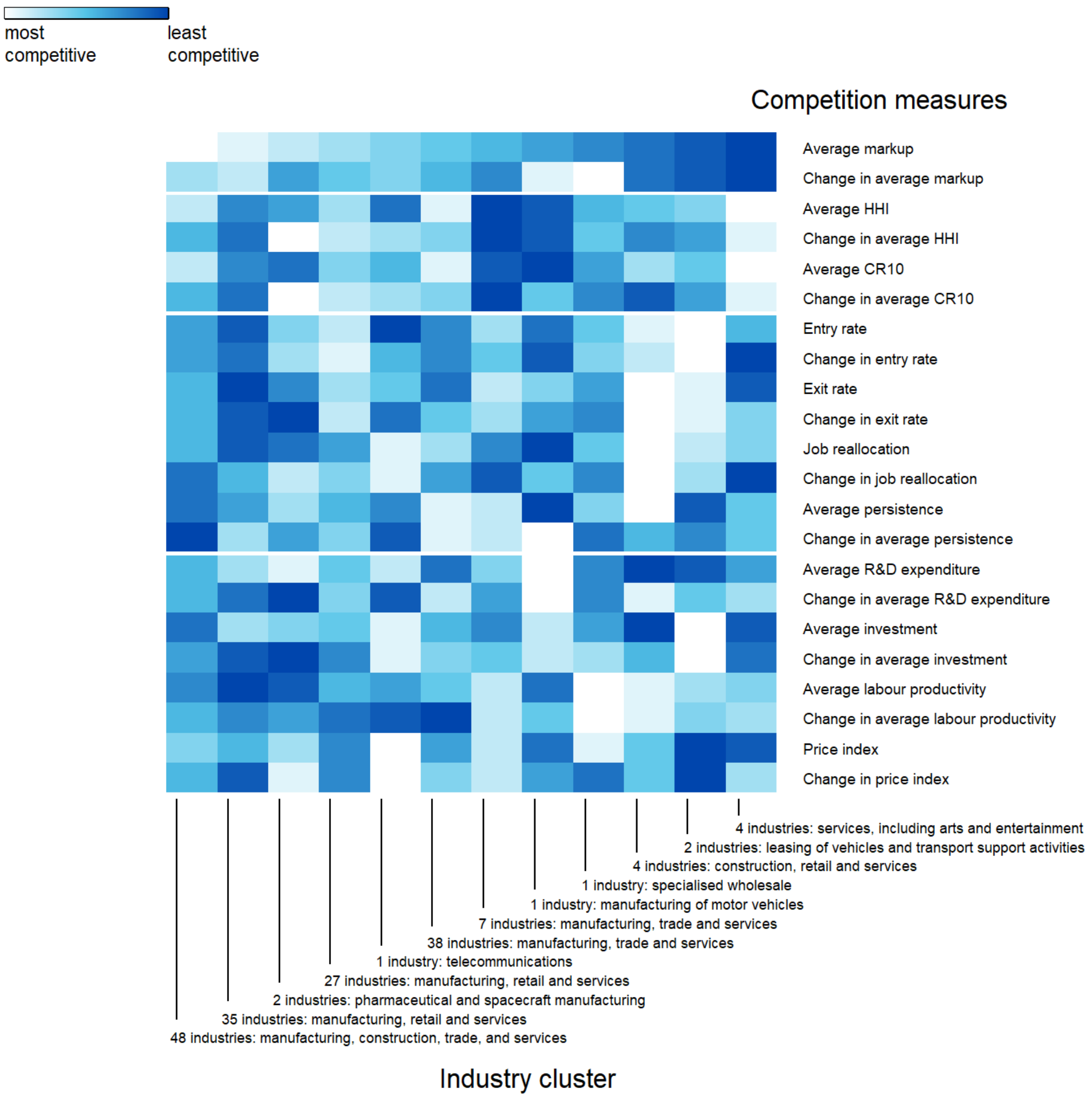
7.52 The cluster with the second highest markups consists of two industries, leasing of motor vehicles and transport support activities. It is characterised by high markup growth, medium-high concentration, high entry rates but large persistence at the top of each industry. Industries in this cluster have high and increasing investment rates.

7.53 The cluster with the highest average concentration measures only features moderate but increasing markups. It consists of a mix of seven manufacturing, trade and services industries, including shipbuilding, the manufacturing of synthetic fibres, the manufacturing of chemical products and activities of call centres. Industries in this cluster are characterised by low job reallocation rates, but relatively high entry and exit rates and high labour productivity.

7.54 At the other end of the markup spectrum, there is a cluster of forty-eight predominantly manufacturing industries (processing of fish, manufacture of bakery products, spinning and weaving, sawmilling and wood manufacturing, manufacture of general-purpose machinery) and some wholesale and services industries. These industries have low and steady markups and low but slightly rising concentration. Despite this, these industries are characterised by stability over time: persistence rates are the highest of any cluster, and entry, exit and job reallocation rates are relatively low.

Figure 54: Industries vary widely in how firms compete in them

Heatmap from a k-means clustering exercise at the three-digit Standard Industrial Classification (SIC) level. Clusters are ordered from lower to higher markup. Data from Annual Respondents Database X (ARDx) 1997-2020, Annual Business Database 2021, Business Enterprise Research and Development survey (BERD) 1995-2017, Business Structure Database (BSD) 1997-2022, Industry level deflators by Office for National Statistics 1997-2023, Longitudinal Business Database (LBD) 1997-2021. GB only



Each cell gives the intensity of competition in each selected measure for a given cluster of 3-digit Standard Industrial Classification (SIC) industries. Darker shades indicate less competition. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to 2005-2017 and excluding SIC sectors: A, B, D, E, K, L, O, P, Q, T, U. Markups are calculated following our baseline approach described in the report. Clusters are ranked by their average markup over that period. Data are 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).

7.55 Table F.3 in the appendix contains a full list of industries in each cluster for readers interested in exploring the picture for specific industries.

7.56 This section shows that it is important to understand the nature of competition at the market or at least industry level across several dimensions. Any one measure might be misleading. For instance, creative arts and entertainment services have seen very high and rising markups despite low and stable concentration levels.

7.57 Ultimately, market-level research and other CMA tools such as market studies are needed to provide the in-depth evidence on competitive behaviour and consumer outcomes at the market level that may allow policymakers to take targeted action.

8 Macroeconomic implications and open questions

8.1 The macroeconomic implications of rising aggregate market power are a lively area of academic research. Economists have argued that rising markups may affect labour demand, the capital share and productivity growth. Estimates of the associated welfare cost range from 2-10% but heavily depend on the assumptions behind the economic models.

8.2 The report concludes by outlining four open questions relevant for policy analysis. First, is the rise in markups due to a rise in prices or a fall in costs? Second, what is the effect of within- and cross-industry ownership networks on market power and the competitive process? Third, how does the rise of the digital economy factor into these macroeconomic trends? And finally, how do these trends break down into individual markets, where competition is product-specific and often local?

The macroeconomic implications of rising markups

8.3 Several recent studies examine how markup trends impact key macroeconomic variables. Syverson (2019), Basu (2019) and De Loecker, Eeckhout and Unger (2020) all provide a good overview of this debate.

8.4 Sales are a fundamental mechanism through which market power can result in macroeconomic impacts. As prices rise due to higher markups, consumers are less inclined to buy goods and services, lowering aggregate demand. This leads to a loss of economic welfare because consumers are unable or unwilling to afford the products they want and need.

8.5 Because they lower aggregate demand, higher markups may also depress the demand for labour inputs, leading in turn to weak growth in jobs and wages and a lower labour share of income. De Loecker, Eeckhout and Unger (2020) and Autor, Dorn, Katz, Patterson and Van Reenen (2020) indeed document a secular decline in the labour share in the US.

8.6 De Loecker, Eeckhout and Unger (2020) emphasize that ex ante, the effect of a rise in markups on welfare may be positive or negative. High-markup firms may be more productive, but at the same time capture more surplus from consumers through their markups and can affect the labour market adversely by pushing down wages.

8.7 To estimate welfare effects, De Loecker and Eeckhout and Mongey (2021), calibrate a general equilibrium model on the time series for markups and labour reallocation between 1980 and 2016. According to the model, the changes in technology and market structure that caused the increased markups have led to an overall 9% decline in US aggregate welfare between 1908 and 2016.

8.8 Döpper, MacKay, Miller and Stiebale (2024) find that observed increases in markups have hurt consumers significantly. In a counterfactual simulation, they find that consumer surplus would have been 14% higher in 2019 if markups were scaled down to 2006 levels.

8.9 Farhi and Gourio (2019) find that the rise in US market power is one of the two key drivers, together with rising macroeconomic risk, of the widening spread between the return on private capital and the risk-free interest rate over the past thirty years. Intangible capital however also plays a significant role and reduces the estimated role of market power once accounted for correctly.

8.10 Some studies have also focused on the macroeconomic consequences of specific competition enforcement policies. Moreau and Panon (2023) build a general-equilibrium model of cartels. Based on a calibration using French data, they estimate that cartels decrease aggregate productivity by about 1% and welfare by 2%.

8.11 Reed, López, Arrieta and Iacovone (2022) study cartels, antitrust enforcement, and industry performance in Mexico. Cartel sanctions lead to productivity increases for all firms in an industry. This suggests that illegal monopolistic practices decrease innovation incentives across all firms in affected industries. Illegal monopolistic practices do not appear to affect the relationship between productivity and market shares, as sanctions do not affect the correlation between market share and productivity or the reallocation of market shares to high-productivity and high-markup firms.

8.12 Some researchers have focused on the effect of aggregate market power on wages. Deb, Eeckhout, Patel and Warren (2023) study how market power in goods and labour markets jointly determines the wage level and the degree of wage inequality.

8.13 They argue that market power in labour markets decreases wages directly while market power in goods markets decreases them indirectly, as higher goods prices cause output and thus labour demand to fall. Based on a calibration using US data from 1997 to 2016, they estimate that the average number of firms per market has strongly decreased while average markups have risen by 30% and wage markdowns have stagnated.

8.14 Deb, Eeckhout, Patel and Warren (2022) suggest that the rise in goods market power of firms accounts for 75% of the observed wage stagnation since the 1980s and explains the decoupling of productivity and wage growth in the US. While both monopoly and monopsony power are present, the former is increasing over this period while the latter is stable. Both contribute to the decoupling of productivity and wage growth, monopoly being the primary determinant.

8.15 Ferrari and Queirós (2024) study how changes in fixed costs and productivity differences between firms relate to the likelihood of economic slumps and measures of market power. They argue that rising productivity dispersion over the past decades, combined with higher fixed costs, simultaneously explains slower post-recession recoveries and observed trends in market power.

8.16 Assessing competition and market power across the whole economy is a daunting task. Estimating the overall effect on consumers and workers, via the many proposed channels and complex dynamic effects, is even more difficult. Nonetheless, research is progressing our understanding of the benefits of competition, and the costs of market power, beyond the narrow market in which it is exercised.

Open questions

8.17 This report has brought together the evidence on the state of UK competition available as of May 2024. Across the whole economy, average markups have risen, driven largely by firms at the top of the markup distribution and the services sector. Business dynamism has fallen, both at the top of the average industry (by turnover or markups) and in terms of the entry and exit margin. However, business dynamism has been, if anything, slightly higher in industries with rising markups, suggesting the link between the two trends is not straightforward.

8.18 The report has also documented the UK's continuing move towards services, changes to the production technology that favour capital and a rise in fixed costs and returns to scale in services.

8.19 M&A activity, while also on the rise over the past two decades, is not concentrated in sectors that have seen an increase in markups. In contrast to research findings for the US, the number of competition enforcement cases in the UK has not fallen over the past decade.

8.20 Finally, the report shows that the rise in markups at the industry level has not been related to higher or lower investment, innovation, R&D or price changes. Productivity is positively associated with markups at both the industry and firm level.

8.21 Despite this new evidence, important open questions remain. First, is the rise in markups due to a rise in prices, or a fall in costs? If it is the former, is it due to better products on average or a rise in firms' ability to appropriate more of the consumer surplus?

8.22 The standard production function methods used to estimate markups are not well suited to answer these questions. Therefore, future research should follow recent studies by Döpper, MacKay, Miller and Stiebale (2024), De Loecker and Scott (2022) and Hahn (2024) in bringing together the benefits of traditional industrial organisation demand estimation methods and production function estimation tools.

8.23 There is also a need to supplement whole-economy studies like this report with smaller-scale, more traditional industry studies that allow researchers to make more realistic assumptions about how firms compete, set prices, and innovate.

8.24 Second, this report barely scratches the surface when it comes to understanding the importance of production linkages and ownership linkages across the economy. Future work by researchers in government and academia might try to understand how supply chain bottlenecks create market power, and how they can be avoided.

8.25 The identity of owners and the degree of common ownership also needs to be understood much more thoroughly. Even the simple descriptive analysis of ownership networks in the UK in ongoing CMA work could be helpful to policymakers across the UK government.

8.26 Third, the digital sector, while a big and growing part of the economy, only features in the background of this report. This is because the tools in this report are well suited for understanding the average outcomes of many similar firms, and less the handful of large multinationals that populate the digital sector. The CMA has already produced work on aspects of the digital economy, from mobile browsing (CMA, ongoing) to AI foundation models (CMA, 2024). Such work provides a more detailed understanding of how these markets work. More studies of the digital sector, by researchers and government analysts alike, are sorely needed.

8.27 Finally, the Standard Industrial Classification (SIC) of economic activities does not necessarily capture the nature of competition well. Often, consumers consider two products substitutes that are not part of the same industry. For instance, the alternative to buying a new bike may be a bus pass. The reverse is also true. Even where firms compete within product markets, evidence suggests these are usually smaller than even the lowest level of the SIC industry classification.

8.28 Moreover, companies often compete locally. For many goods and services, these local markets can be quite small. Due to data limitations, this report abstracts completely from these issues, but we hope that data providers in the UK will continue to improve data sources so that future iterations of the State of UK Competition report will be able to present a more nuanced picture of competition and market power in the UK economy.

A. Acknowledgements

A.1 This report was written by Amanda Ereyi, Fizza Jabbar, Joel Kariel, Luke McWatters, Rajssa Mechelli, Max Read, Jakob Schneebacher and Nicole Scholz on behalf of the CMA Microeconomics Unit. Mark Le Quement surveyed the relevant literature.

A.2 This report uses Office for National Statistics (ONS) statistical research datasets via the Secure Research Service (SRS). Outputs may not exactly reproduce National Statistics aggregates. We are grateful to SRS staff for their help and advice. The report also uses aggregate data from the ONS website.

A.3 Chapter 6 uses data from the Competitiveness Research Network (CompNet) distributed microdata projects at IW Halle. We thank the CompNet team, in particular Tommaso Bighelli and Javier Miranda, for their help, and the national data providers for supporting the CompNet project.

A.4 The authors are very grateful to Steve Bond, Giacinta Cestone, Diane Coyle, Basile Grassi, Paolo Mengano, Nathan Miller, Simon Mongey, Aureo De Paula, Anthony Savagar, Riccardo Silvestrini, Howard Smith, Joel Stiebale, John Van Reenen and many CMA colleagues for their feedback on methods and results, to Frank Donnarumma for feedback on data visualisations, and to Gavin Thompson for help and advice on drafting.

B. Glossary

B.1 **Berry ratio:** The Berry ratio compares a firm's gross profit to its operating expenses. The ratio can tell us about the financial health of the firm, and in particular its ability to meet its expenses out of the revenue it generates. A ratio of 1 or above indicates that a firm's profits are higher than its operating expenses, while a ratio below 1 indicates the that its operating expenses exceed its profits.

B.2 **Business dynamism:** Business dynamism refers to degree of churn in an economy. It encompasses factors such as the birth, growth, decline, and exit of firms and the creation and destruction of jobs. High levels of business dynamism can indicate a vibrant and competitive economy where new ideas and innovations are constantly introduced and resources such as capital and labour reallocated to their most productive use. We measure business dynamism in four ways; entry and exit rates, job reallocation rates, persistence of large firms over time, and the share of turnover and employment accounted for by young firms.

B.3 **Cost markups:** Cost markups are defined as the difference between the price at which a good or service is sold and its marginal cost (or, more often in this report, their ratio). Cost markups are a measure of market power. In a perfectly competitive market markups are close to zero (to one when defined as a ratio), meaning firms set their prices equal to their cost of production. 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.4 **Common ownership:** In general, two firms are commonly owned when one or more of their owners have shares in both. Where owners own significant shares in more than one firm in a given market (or closely related markets), common ownership may influence the incentives of firms to compete. In this report, we construct ownership links for ownership stakes above 25%. This does not account for smaller stakes, like those often held by large passive investors such as mutual funds.

B.5 **Elasticity:** An elasticity is a common way to measure the relationship between two economic variables. An elasticity measures the percentage change in one variable associated with a one-percent change in the other. Within this report, we use elasticities for instance to capture the responsiveness of output to changes in capital, labour, and material inputs.

B.6 **Extensive and intensive margins:** Economists refer to the decision to take an action at all as the "extensive margin" and to the decision how much to do as the “intensive margin”. For instance, in this report, we measure the extensive and intensive margins of research and development (R&D): the decision to engage in R&D at all and the amount of spending for firms that engage in any R&D, respectively.

B.7 **Herfindahl-Hirschman Index (HHI):** The Herfindahl-Hirschman Index (HHI) is one common way to measure the concentration in a market or industry. It is calculated by summing the squared market shares of each firm competing in a market. By squaring the market shares the HHI measure gives greater weight to larger firms. The HHI can range from zero for a perfectly competitive market to a maximum value of 10,000 for a monopolistic market. A market is generally said to be concentrated if the HHI is above 1,500 and highly concentrated if HHI is above 2,500.

B.8 **Liquidity ratio:** The liquidity ratio measures a firm ability to pay its short-term debt obligations. It gives an indication of the financial health of the firm.

B.9 **Marginal costs:** The marginal cost is the cost of producing an additional unit of a good or service.

B.10 **Market concentration:** Market concentration is the degree to which a small number of companies control a large part of the sales in a market. When market concentration is high, it indicates only a few firms dominate the market. This may be the case in in oligopolistic or monopolistic competition. Conversely, low market concentration can indicate a more competitive market structure. However, other factors like production technologies also influence the concentration of a market. In this report, we compute two measures of concentration: concentration ratios (CR_n) and the Herfindahl-Hirschman Index (HHI).

B.11 **Market power:** Market power refers to the ability of a firm, or a group of firms, to influence the price of goods or services in a market. In economic theory, market power is associated with the firm’s ability to set prices above its marginal costs, and therefore higher than they would be in a competitive market. Market power can come from a cost advantage, a strong brand, the creation of a product consumers like or from the creation of barriers to entry and the acquisition of rival firms.

B.12 **Network effects:** Network effects refer to the concept that the value of the product or service rises in tandem with the number of users. Network effects can be very strong in digital industries, where platforms connecting users to each other play an important role.

B.13 **Production function approach:** The production function approach is one way to estimate the difference between prices and marginal costs. Since marginal costs are generally unobservable, this approach backs out markups from the production decisions of the firm. This requires some assumptions about the firm's objectives and constraints, and how firms transform inputs into output. Appendix D explains these assumptions in more detail.

B.14 **Productivity:** Productivity measures how efficiently firms, industries or economies convert inputs into outputs. Economists refer to either the productivity of individual factors of production (such as labour, capital) or of all factors combined. The latter is called total factor or multifactor productivity. It is difficult to measure total factor productivity (TFP) directly, therefore it is typically derived as the residual change in output not due to changes in observable inputs. In this report we also measure labour productivity, either expressed as turnover per employee or turnover per hour worked.

B.15 **Selling, General and Administrative (SG&A) expenses:** Selling, General and Administrative (SG&A) expenses are a catch-all category of non-production costs. Examples of SG&A items include marketing, advertising, personnel, and utilities. In this report, we approximate SG&A expenses by subtracting earnings before interest, taxes, depreciation, and amortization (EBITDA) from gross profits.

B.16 **Wage markdowns:** Wage markdowns are defined as the difference between the additional contribution a worker makes to a firm's revenue and the wage she receives. This is a measure of employer market power: the larger the markdown, the less of the surplus created together goes to the worker.

C. Data sources

Primary microdata sources

C.1 The Annual Respondents Database X (ARDx; 1997-2020) and the Annual Business Survey (ABS; 2021) are the two main data sources used for markup estimation.

a) The ABS (which replaced the Annual Business Inquiry in 2009) is the Office for National Statistics' (ONS) largest business survey, with around 62,000 questionnaires sent out across Great Britain and around 600 questions asked every year.

b) The ABS's sampling scheme aims to produce best estimates of the population totals from a random sample stratified by Standard Industrial Classification (SIC), employment, and country using the information from the Inter-Departmental Business Register (IDBR). The sampling scheme selects all the largest businesses with a progressively smaller fraction of smaller businesses.

c) The survey collects variables such as the total value of sales, the value of purchases of goods, materials and services, capital expenditure, and total employment costs that are key to the analysis in this report.

d) The ARDx is a research dataset created by the ONS from two surveys: the Annual Business Inquiry for the period 1997-2008 and the ABS (supplemented with employment data from the Business Register and Employment Survey) that replaced the ABI from 2009. The ARDx is complemented by the ARDx Capital Stock dataset that provides estimates of the reporting units' level of capital stock generated using the Perpetual Inventory Method.

e) The Business Structure Database (BSD; 1997-2023) contains information on employment, turnover, foreign ownership, industrial activity and year of birth and death for almost all businesses in the UK. The BSD is primarily derived from annual snapshots of the IDBR. The BSD is used for the estimation of concentration, persistence, and turnover weights.

C.2 The Inter-Departmental Business Register (IBDR) is a live registry of UK businesses used as the main sampling frame for business surveys carried out by the ONS or other government departments. The main sources of input for the IBDR are Value Added Tax (VAT) and Pay As You Earn (PAYE) records from HMRC. The IDBR represents 97% of turnover and 88% of employment in the UK. Very small businesses that do not meet the thresholds for VAT or PAYE may not be included in the IBDR.

C.3 The Longitudinal Business Database (LBD; 1999-2022) contains longitudinal information on the structure and activity of businesses at a quarterly frequency. The LBD is primarily derived from quarterly snapshots of the IDBR. The LBD provides longitudinal information by using consecutive snapshots from the IDBR to deduce changes to business structure and continuity of business activities. The LBD is used for estimates of entry and exit, job reallocation and some M&A analysis.

C.4 The Mergers and Acquisitions Survey (M&A survey; 2013-2021) provides information on the timing, value and number of funding methods of merger and acquisition transactions involving UK businesses with deal values of transaction values of £1 million and above. Since January 2018, the sampling source for the survey has been Bureau van Dijk's Zephyr database. Before January 2018, information on M&A deals was acquired from financial press, specialised publications, websites specialising in M&A and the websites of businesses regularly engaged in M&A activity.

Secondary microdata sources

C.5 The Business Expenditure on Research and Development (BERD; 1995-2021) is an ONS annual survey that provides information on total Research and Development (R&D) expenditure in the UK by business enterprises, total R&D employment and sources of funds.

a) Due to sampling and disclosure control issues, we exclude waves of BERD before 2002. We also exclude waves after 2017, since the available data after 2017 cannot be weighted to be representative of the wider R&D population.

C.6 Companies House is responsible for incorporating and dissolving limited companies in the UK and maintains a register of these companies. This data is used to plot the density of common and cross-ownership for incorporated UK businesses.

C.7 The Competitiveness Research Network dataset (CompNet, 1997-2021) is a micro-aggregated dataset of indicators of competitiveness and productivity for twenty European countries. 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.8 The FAME database (2005-2021), provided by Bureau van Dijk, contains information on over fifteen million companies in the UK and Republic of Ireland.

FAME contains firm-level data on company financial accounts, activities, ownership, and other firm characteristics for large public and private companies (with turnover above £1.5 million, profits above £150,000 or shareholder funds above £1.5 million) and summary information for remaining smaller businesses. The database covers the last 10 years, for both dormant and active companies, and is updated daily from information from Companies House.

Industry-level data sources

C.9 Business investment by industry and asset (1997-2023) is an ONS dataset that provides a detailed breakdown of UK business investment by industry and asset.

C.10 GDP output approach – low-level aggregates (1990-2023) is an ONS dataset that provides estimates of UK output gross value added.

C.11 Industry deflators (1997-2023) is an ONS dataset that provides a mix of product and implied industry level deflators.

C.12 ONS Input-output tables (2013-2019) provide information about flows of goods between industries. The ONS provides Leontief inverse matrices, and we use these to calculate industry-level upstreamness in each year. A Leontief matrix shows the amount of inputs needed in each sector to produce one unit of output.

C.13 Labour productivity by industry division (1997-2021) is an ONS dataset that provides productivity hours and output per hour by industry division.

C.14 The following ONS datasets provide domestic output price indices:

a) producer price inflation time series (2009-2021)

b) services producer price inflation time series (2009-2021).

C.15 The following ONS datasets provide breakdowns of UK trade in goods and services on a balance of payments basis: UK trade in goods by industry, country and commodity, exports (2016-2021), UK trade in services by industry, country and commodity, exports (2016-2021), UK trade in goods by industry, country and commodity, imports (2016-2021) and UK trade in services by industry, country and commodity, imports (2016-2021).

Industries included

C.16 In most of the analysis, unless otherwise indicated, we exclude SIC sectors that are not suitable for the production function estimation of markups. These are

SICs dominated by public-sector firms or where firms are believed not to follow the standard cost-minimizing behaviour required by the method.

C.17 We therefore exclude SIC sections A (agriculture, forestry and fishing), B (mining and quarrying), D (electricity, gas, steam and air conditioning supply), E (water supply; sewerage, waste management and remediation activities), K (financial and insurance activities), L (real estate activities), O (public administration and defence; compulsory social security), P (education), Q (human health and social work activities), T (activities of households as employers; undifferentiated goods-and services-producing activities of households for own use), and U (activities of extraterritorial organisations and bodies).

D. Methodology

Cost markup estimation

D.1 Cost markup is the ratio between the price at which one unit of good/service is sold and its marginal cost.

D.2 When computing the cost markup, the general problem faced is that marginal costs are not observed directly. Different approaches have been proposed to overcome this problem. In this report, we rely on several specifications of the production function approach to obtain many estimates and be sure that our results are not driven by the specific method chosen.

D.3 Under the production function approach as originally proposed by Hall (1988) and extended by Warzynski and De Loecker (2012), the idea is to start from the cost minimisation problem of the firm. The firm's optimality conditions imply an equality between the markup (μ_{it}) and the ratio between the output elasticity of each variable input (in short output elasticity, θ_{it}^{V}) and the input's share of revenue $\mu_{it} = \theta_{it}^{V} / \frac{P_{it}^{V} V_{it}}{P_{it} Q_{it}}$, where V denotes the variable input considered.

D.4 The method makes no assumptions on the nature of the demand function and the obtained equality holds true whatever the assumed mode of competition. Furthermore, the equality is valid for every variable input, so the markup can be obtained without making any assumptions about input substitutability.

D.5 The equation discussed above allows us to get rid of the marginal cost in the definition of markup. However, while the input's share of revenue is quite easily observed in most data sets, the output elasticity is not and thus needs to be estimated.

D.6 Several approaches have been proposed to estimate the output elasticity, which differ in their sophistication and robustness to assumptions about the variables that affect the firm's output. There are two general approaches, the cost share approach, and the estimation of the production function.

D.7 In the cost share approach, the output elasticity of an input is approximated by measuring the factor's share of total variable costs. This would be the exact result of the cost minimisation problem in the case of a Cobb-Douglas production function where elasticities sum to one (corresponding to the knife edge case of constant returns to scale).

D.8 In the case of a Cobb-Douglas with non-constant returns to scale, the output elasticities can still be retrieved from the cost shares by solving an implied system of linear equations. It is important to note that overall, that the method makes strong assumptions on the production function which can be hard to defend.

D.9 In this report, we instead rely on the estimation of the production function to directly get estimates of the output elasticities. This approach consists in directly estimating a parametric production function, Cobb-Douglas or the more general Translog production functions being prominent examples.

D.10 The most important econometric problem when estimating production functions, is that some independent variables affecting production are not observed by the econometrician but are known to the firm. In such a scenario, if input levels are chosen as a function of these variables, an endogeneity problem arises which will bias the OLS estimates of the function's coefficients.

D.11 Consider the example of a Cobb-Douglas production function which gives rise to the following relation: $y_{it} = \theta_l l_{it} + \theta_k k_{it} + \omega_{it} + \epsilon_{it}$. Here, y_{it} is the log of output by firm *i* at time *t*, l_{it} is the log of labour input, k_{it} is the log of capital input. Productivity is captured by the sum $\omega_{it} + \epsilon_{it}$. The component ϵ_{it} corresponds to shocks to productivity that are not observable by firms before making their input choices (e.g. equipment breakdown). The term ω_{it} instead identifies productivity shocks that are observed by the firm before choosing l_{it} and k_{it}, but not by the econometrician (e.g. managerial skills in the firm).

D.12 A simple OLS estimation of the equation above would likely yield biased estimates for the coefficients θ_l and θ_k because ω_{it} (productivity observed by the firms but unknown to the researcher) has an impact on the firm's chosen level of capital and labour inputs.

D.13 A widely used family of methods to address the issue is known as the control function (or proxy function) approach. Early proponents of this approach are Olley and Pakes (OP, 1996) and Levinsohn and Petrin (LP, 2000).

D.14 The key assumption in these approaches is that firms choose levels of the labour or investment after observing productivity shocks (that researchers cannot observe). Therefore, these choices contain information about the realised productivity. The firm's optimal input decision can be inverted to retrieve the productivity shocks and the coefficients of interest can be estimated in a second stage of the process.

D.15 These approaches rely on several structural assumptions and there is a wide debate in the economic literature about their validity and their shortcomings. Their application however has grown substantially in the recent decades, and extensions or alternative methods stemming from them have been developed.

D.16 Ackerberg, Caves and Frazer (ACF, 2015) is one example of refinements of the control function approach, trying to solve potential collinearity issues arising with LP or OP.

D.17 A prominent critique of ACF is that it does not account for the fact that firms often have market power. De Loecker and Warzynski (2012), De Loecker, Goldberg, Khandelwal and Pavcnik (2016), De Loecker, Eeckhout and Unger, (2020) and De Loecker and Scott (2022) are among the examples of applications of the ACF methodology controlling for imperfect competition in product markets. In practice this often amounts to adding more control variables (so-called input demand shifters) in the function that determines the demand for intermediate input as a function of privately observed productivity shocks.

D.18 Another prominent critique of these methods is that researchers often use revenue data instead of output quantities in their estimation. Bond, Hashemi, Kaplan and Zoch (2021) show with the use of an econometric model that this can cause severe bias.

D.19 De Ridder, Grassi and Morzenti (2024) offer a discussion of the reliability of these methods when quantity data are not available and find that the revenue-based markups are still strongly correlated to the true ones. They also provide adjustments that allows to proxy for market power in the estimation process.

D.20 Kirov, Mengano and Traina (2023) also produce Markup estimates for an environment with market power and based on revenue data. Their proposed methodology involves introducing a control function for markups instead of a control function for privately observed productivity.

D.21 An alternative avenue to production function (i.e. output elasticity) estimation is the dynamic panel approach (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998; Blundell and Bond, 2000). The method has the advantage of completely circumventing the issue of finding and inverting an input function (as in the control function approach) but requires strong assumptions about the process that the privately observed productivity shocks follow.

D.22 In this report, we rely on the production function approach. Our baseline estimates of markup come from an OLS estimation of a translog production function, estimated at a SIC two-digit level.

D.23 To estimate markups, we rely on data from the ARDx (for the period 1997-2020) and the ABS (2021). We select intermediate consumption (that is, materials) as the variable input in the production function.

D.24 Pre-estimation cleaning of the firm-level data includes trimming the top and bottom 1% observations for capital share, labour share and intermediate consumption share. We also drop the observations that – once converted to logarithms - have negative values for capital, employment, turnover, value added, intermediate consumption, labour cost and investment.

D.25 We also test several alternative specifications all based on the production function approach. Specifically, we provide:

a) OLS estimation of a Cobb-Douglas

b) ACF and DGM estimation of a translog production function (for comparability with the baseline)

c) Estimates obtained with the cost-share approach implemented on FAME data (provided in the appendix).

D.26 Firm-level markup estimates obtained with any of the specifications above are then cleaned of the outliers (top and bottom 1% in each two-digit industry) and averaged to obtain the aggregate industry level markup. In our baseline case, we use firms' turnover as an aggregation weight. We also produce alternative aggregations, including unweighted averages and value-added and labour cost weighted averages. The most common levels of aggregation we use in the analysis are SIC two-digit, SIC sectors, and economy-wide. However, in some cases we also report measures aggregated to SIC three-digit (e.g. in the cluster analysis).

D.27 It is important to note that the production function approach that we employ is not the only method proposed in the literature to estimate markups.

D.28 A very simple alternative is the so-called accounting approach, that estimates markups directly by dividing revenue by total costs. This relies on the very strong assumption that returns to scale are constant, i.e. that marginal costs equal average costs. Given the unrealistic assumption, and the more recent developments in this literature, this method is not anymore widely used by economists and therefore we do not implement it in this report.

D.29 The demand approach (see Berry, Levinsohn, and Pakes 1995; Bresnahan 1989) is another potential alternative to the production function approach. It requires the researcher to assume a specific demand function and an explicit model of competition among firms combines (Betrand, Cournot, possibly allowing for some collusion, etc…). The method then combines the firm's profit maximisation problem and the demand function estimation to get estimates of the markup.

D.30 More specifically, the firm's optimal price setting problem yields an equality between the so-called Lerner index (a common measure of firms' market power ranging between 0 and 1) and an expression involving the inverse of the price elasticity of demand. Given information about the products prices and quantities and estimates of own and cross price elasticities, this can be used to retrieve the marginal cost and thus the price to marginal cost ratio.

D.31 The little availability of data on prices and quantities at the product level for such a large number of sectors as we consider in the report make the demand approach unfeasible for our need.

Cost markup decomposition

D.32 We follow De Loecker, Eeckhout and Unger (2020) in decomposing changes in aggregate markups over time. The annual change in the economy-wide weighted-average markup can be expressed as the sum of three terms: (1) changes *within* sectors, (2) changes *between* sectors, (3) *reallocation*. The within effect describes changes in markups at the industry level. The between effect describes economic activity shifting between sectors with different levels of markups. The reallocation effect is the joint change in industry markups and industry shares.

$$\Delta\mu_t = \sum_i s_{i,t-1}\ \Delta\mu_{i,t} + \sum_i \Delta s_{i,t}\ \mu_{i,t-1} + \sum_i \Delta s_{i,t}\ \Delta\mu_{i,t}$$

D.33 The above equation shows how the change in the weighted-average markup is equal to the sum of the within, between and reallocation effects. Each effect is summed over all industries, denoted with the subscript i . The within effect isolates changes in within-industry markups, holding industry shares s_i constant. The between effect isolates shifting economic activity across sectors, holding markups μ_i constant. The reallocation effect combines joint changes in shares and markups.

Concentration

D.34 We use two measures of concentration in our report: Concentration Ratios (CR_n) and the Herfindahl-Hirschman Index (HHI).

D.35 The CR_n is calculated by summing the market shares of the n largest firms at a given level of aggregation (for instance, a market or an industry). Commonly used concentration ratios include CR5 and CR10, which measure the total market share of the five and ten largest firms, respectively.

D.36 The HHI is calculated as the sum of the squares of the market shares of all firms at a given level of aggregation. The HHI ranges from 0 to 10,000, with 0 representing a perfectly competitive market and 10,000 representing a monopoly. Often, markets with a HHI exceeding 1,500 are deemed moderately concentrated, while those with a HHI exceeding 2,500 are deemed highly concentrated.

D.37 In the report, both measures are computed at the four-digit SIC level and are aggregated up to whole-economy or sectors by weighting for industry turnover. For both measures of concentration, annual turnover data is used to calculate market shares comes from the Business Structure Database (BSD).

Entry and exit

D.38 Entry and exit rates are estimated using local units and single-site enterprises on the Longitudinal Business Database (LBD). Enterprises are organisational units that produce goods and services and have a certain degree of autonomy in decision making. Local units are individual sites (establishments) belonging to an enterprise. We define single-site enterprises as enterprises that do not have local units for the entirety of their existence on the LBD. These are also included in our count of local units.

D.39 The entry rate is defined as the number of entrants divided by the total number of active local units in the previous quarter. The exit rate is similarly defined as the number of exits divided by the total number of active local units in the previous quarter.

D.40 Entry and exit rates are estimated quarterly and aggregated to annual rates by summing the number of entries and exits over the four quarters then dividing by the average number of active local units the four quarters prior.

D.41 We define as entry both the first appearance of a local unit and its reactivation. Similarly, we define as exit a local unit in the last quarter before disappearing from the LBD, one that appears with a death marker for the first time or one that becomes inactive.

D.42 Entry and exit rates estimated at the Standard Industrial Classification (SIC) industry level also consider changes in SIC codes as entries into and/or exits from the industry. The analysis on entry and exit is only carried out on active firms. A local unit is considered active if a) it is an entrant or b) it appears in the LBD with an active activity marker and it is not classified as an exit in that quarter.

Job Reallocation, Creation and Destruction

D.43 Job reallocation, creation and destruction rates are estimated using reporting units on the Longitudinal Business Database (LBD). Reporting units are linked to enterprises and hold mailing addresses to which ONS surveys are sent. The response from reporting units can cover an enterprise or parts of the enterprise (defined by clusters of local units). For most businesses, the reporting unit is the same as the enterprise. However, some larger businesses or businesses with more complex structures have multiple reporting units that cover different parts of the enterprise.

D.44 The analysis is carried out on active firms. A reporting unit is defined active if a) it is an entrant or b) it appears in the LBD with an active activity marker and it is not classified as an exit in that quarter.

D.45 The job reallocation rate is defined as the sum of the job creation and job destruction rates. The job creation rate is the sum of positive employment changes from one quarter to another divided by total employment of active reporting units the quarter before. The job destruction rate is the sum of negative employment changes from one quarter to another divided by total employment of active reporting units the quarter before.

D.46 These rates can further be decomposed into job creation by entry, job destruction by exit and job creation and destruction by incumbents. Job creation by entry is the sum of employment created by newly established reporting units. Job destruction by exit is the sum of employment lost because of exiting reporting units. Job creation and destruction by incumbents are respectively the positive and negative changes in employment for reporting units that remain active on the LBD over two consecutive quarters.

D.47 For the decomposition above entry and exit of reporting units is defined as for local units. More details in the “Entry and exit” section above.

D.48 Job reallocation, creation and destruction rates are estimated quarterly and aggregated to annual rates by summing job reallocation, creation, and destruction over the 4 quarters then dividing by the average of total employment of active reporting units the 4 quarters prior.

Mergers and Acquisitions from the Longitudinal Business Database

D.49 We use the Longitudinal Business Database (LBD) to get an estimate of the number of Mergers and Acquisitions (M&A) that occur each year.

D.50 Our main definition of M&A events considers movements of local units (establishments) to a different enterprise (new or already existing). We also compute movements of establishments to different reporting units as an alternative measure.

D.51 With the LBD, we get quarterly estimates of M&A. We then sum events over the four quarters to get annual estimates.

D.52 As well as M&A, this measure will include some movements of local units to new enterprise/reporting units which occur because of administrative changes. This measure should therefore be interpreted as an upper bound estimate of M&A activity.

Cluster Analysis

D.53 The cluster analysis divides industries into archetypes based on the full spectrum of market power and market structure measures. It uses a simple k-means machine learning algorithm that takes all the industries and divides them into an increasing number of groups to minimise the unexplained variation in our market power measures within groups (Lloyd, 1982). We stop increasing the number of groups once an additional one would not significantly increase the share of variation captured by the clusters.

D.54 We cluster industries across all major competition indicators discussed in the report. They fall into four categories: markups, static concentration measures (HHI and CR10), dynamic competition measures (entry, exit, job reallocation and persistence rates) and four relevant industry-level economic outcomes (R&D, investment rate, productivity, and prices).

D.55 The analysis is done at the three-digit SIC industry level. When a measure is not available for a given three-digit SIC industry, we assign the relevant two-digit SIC average. We exclude merger and acquisition metrics from the analysis because the high number of missing values in these indicators would force us to drop a significant number of industries.

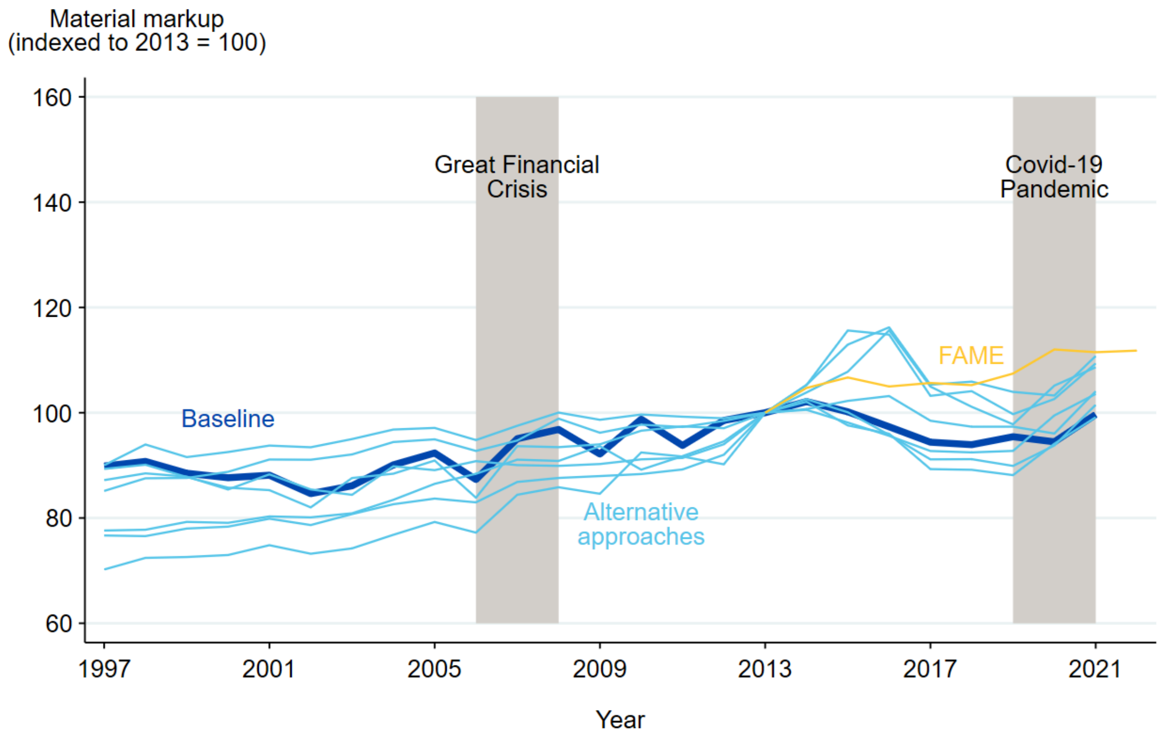
D.56 We base the cluster analysis considering the 2020 level and the total change in the competition measures between 2005 and 2020. The only exception is R&D data, for which we stop in 2017 due to data availability. Before proceeding in the analysis, all metrics are scaled to improve comparability.

D.57 After dropping the observations with one or more unavailable measures, the cluster analysis is done on 166 SIC three-digit industries. Table 3 in Appendix F contains a list of the clusters and all the industries considered.

E. Additional figures

Figure E.1: Average markups in UK have risen since 1997

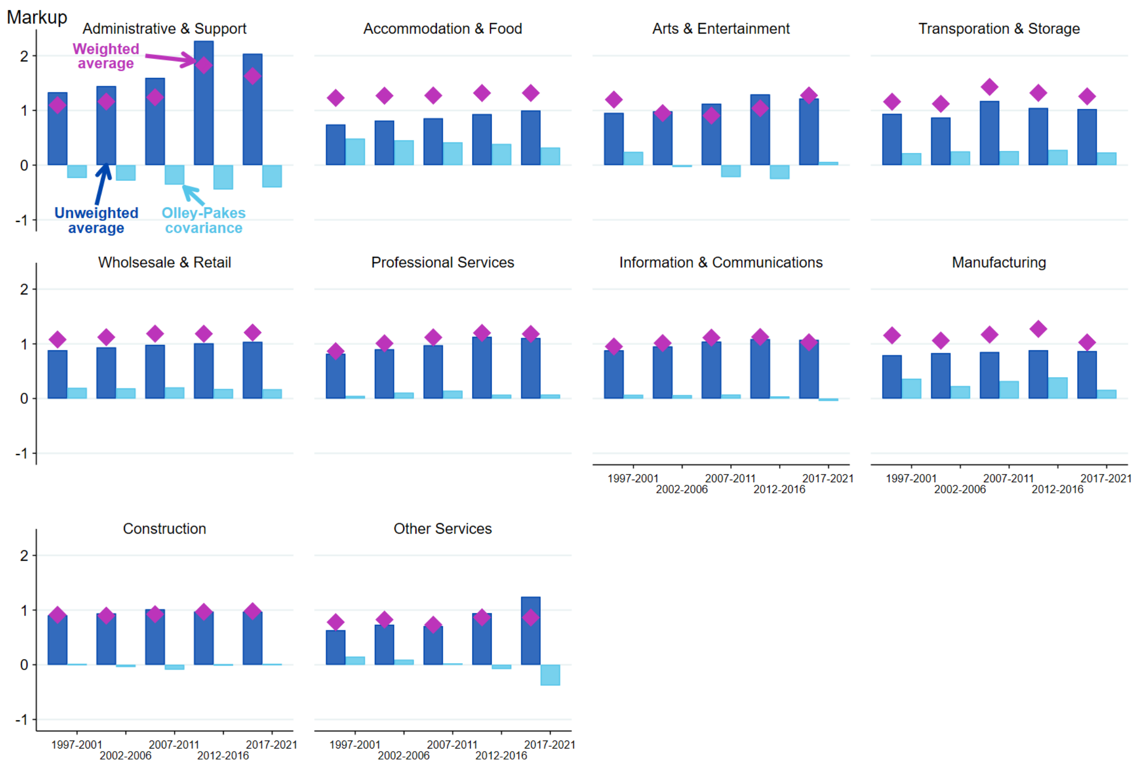
Economy-wide average markup estimates. Baseline measure: Ordinary Least Square (OLS) estimation of a translog production function with materials as flexible input. Firm-level estimates are aggregated weighting by turnover. Data from Annual Respondents Database X (1997-2020), Annual Business Survey (2021) and Bureau van Dijk's FAME (2013-2022). FAME data covers the entire UK, other data GB only



Markups are calculated following our baseline approach described in the report. Alternative approaches include different production functions, different aggregation weights and control function estimation methods. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021). Yellow series from *Bureau Van Dijk's FAME* (2013-2022)

Figure E.2: In most sectors, reallocation plays a minor role in the rise of markups

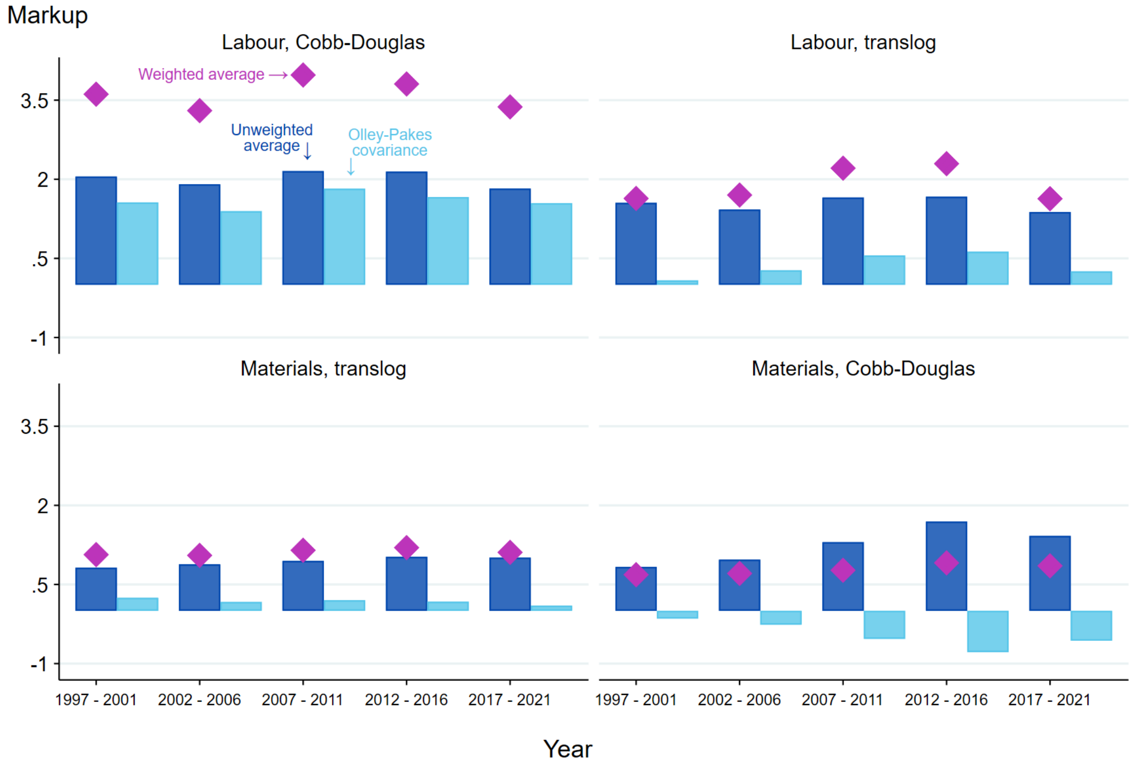
Sectoral markup Olley-Pakes decompositions. Estimates are averaged over sub-periods. Markups computed using Ordinary Least Square (OLS) estimation of a Translog production function with materials as flexible input. Data from the Annual Respondents Database X (1997-2020) and Annual Business Survey (2021). Data covers GB only



Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Olley-Pakes decompositions averaged over sub-periods. Industries are ranked by their weighted markup in the period 2017-2021. Data from the *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021).

Figure E.3: Reallocation is roughly stable over time, but its importance varies with the specification considered

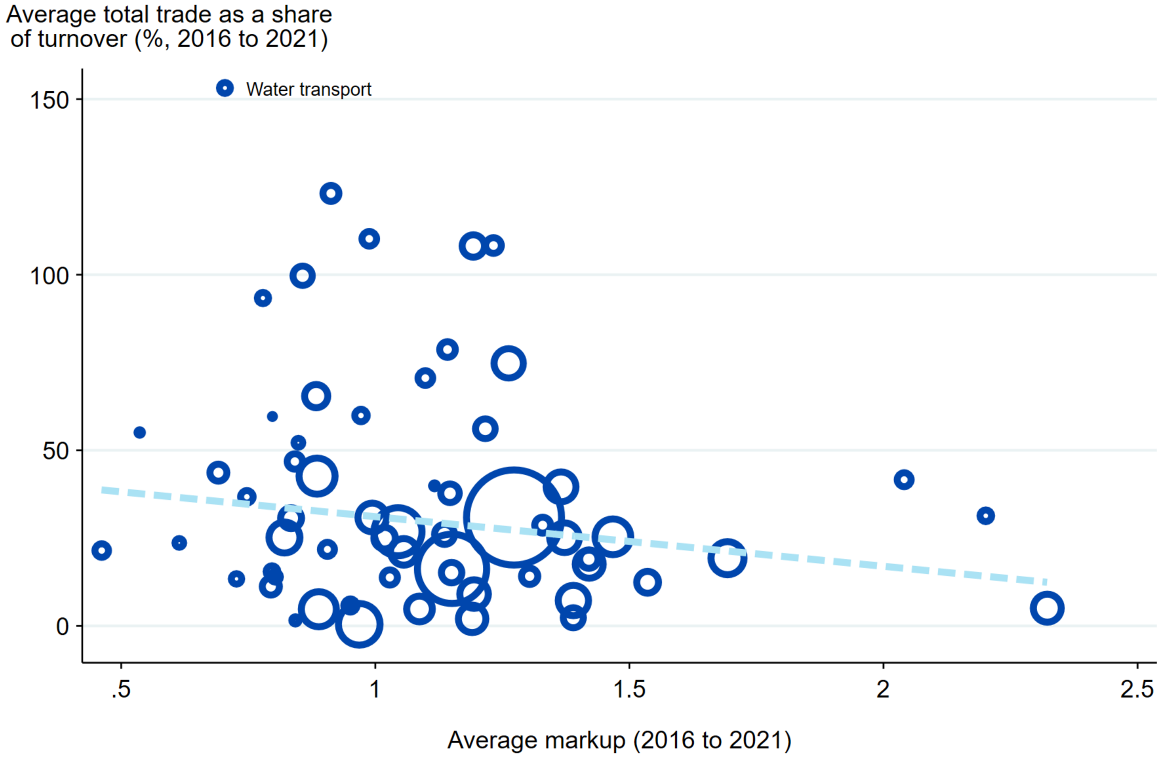
Olley-Pakes decomposition of aggregate markup computed under various specifications (production function: Cobb-Douglas or translog, variable input: labour or materials). The estimates are averaged over sub-periods. Data from Annual Respondents Database X (1997-2020) and Annual Business Survey (2021). Data covers GB only



Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Olley-Pakes decompositions averaged over sub-periods. Industries are ranked by their weighted markup in the period 2017-2021. Data from the *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021).

Figure E.4: Relative total trade and markups are not correlated

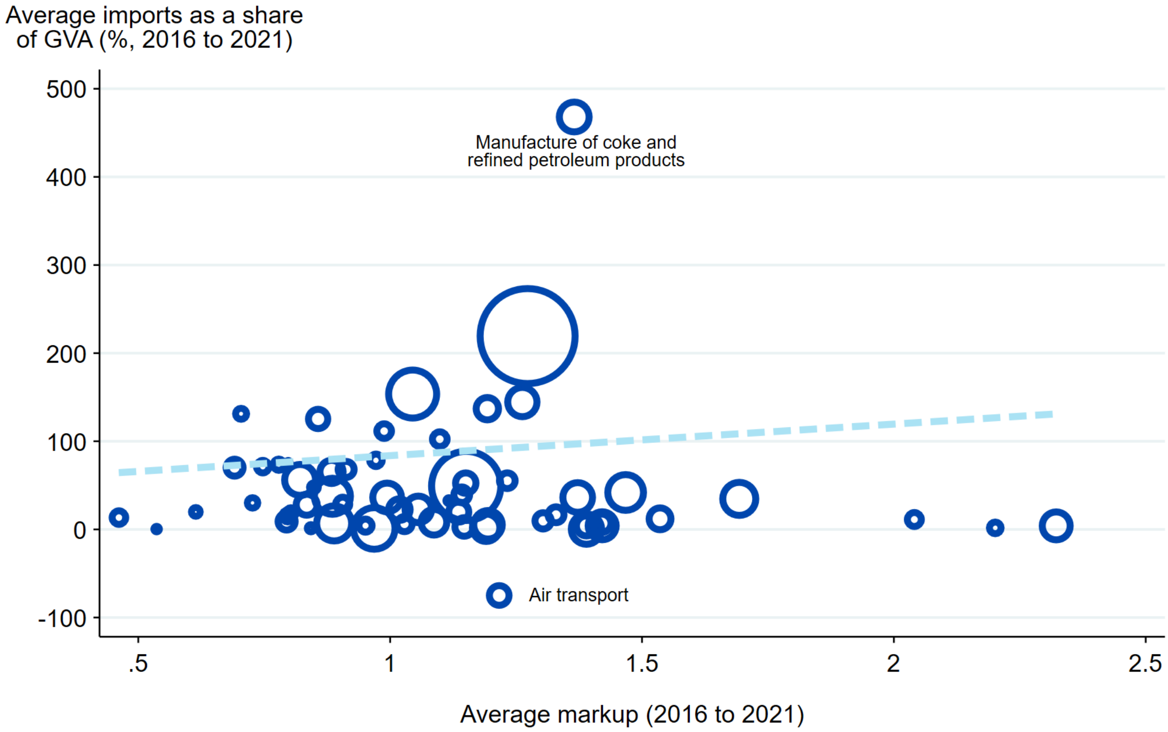
Scatterplot of the average value of total trade relative to turnover against average markups at the two-digit Standard Industrial Classification level between 2016 and 2021. Data from Annual Respondent Database x (2016-2020), Annual Business Survey (2021), Business Structure Database (2016-2021) and ONS UK Trade in services/goods by industry, country, and service type (2016-2021)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fit weighted by turnover and is not statistically significant at the 5% level (as represented by the dashed line). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and 2-digit sectors that we do not have data for in every single year. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), *ONS UK trade in services/goods by industry, country and service type, imports* (2016-2021) and the *Business Structure Database* (1997-2022).

Figure E.5: Relative import expenditure and markups are not correlated

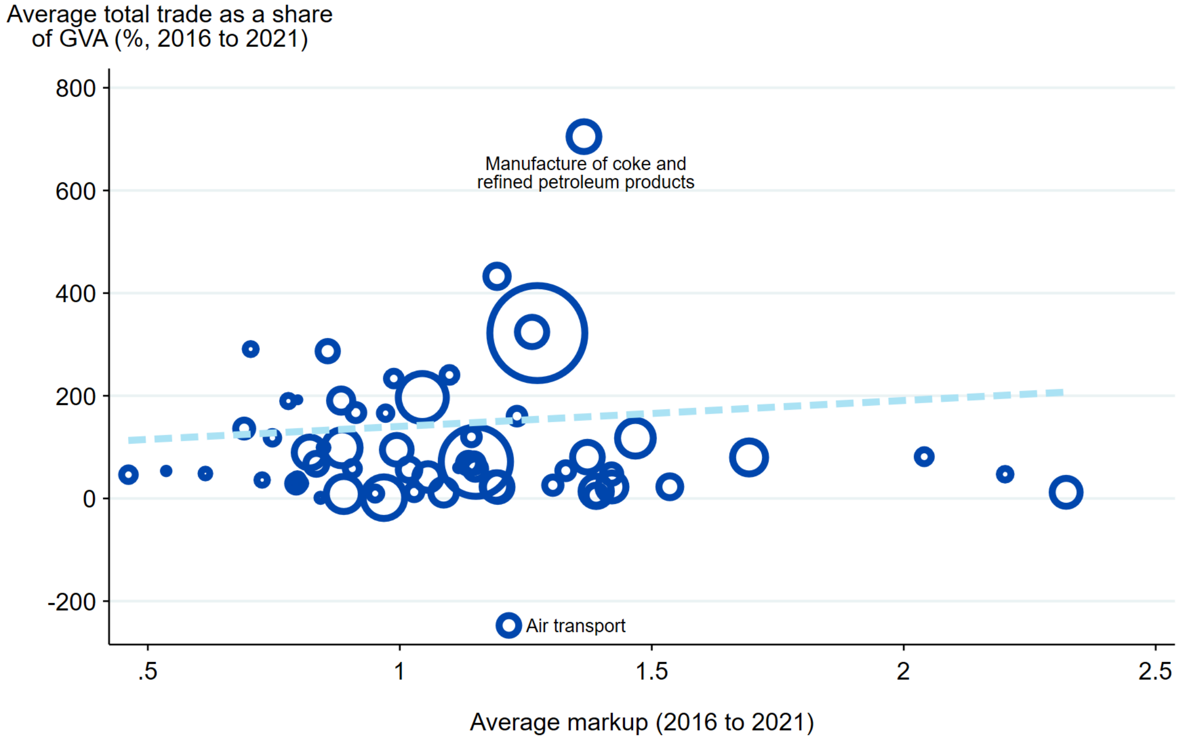
Scatterplot of the average expenditure on imports relative to gross value added against average markups at the two-digit Standard Industrial Classification level between 2016 and 2021. Data from Annual Respondent Database X (1997-2020), Annual Business Survey (2021), Business Structure Database (1997-2022), ONS GDP Output Approach (2016-2021) and ONS UK Trade in services/goods by industry, country, and service type (2016-2021)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fit weighted by turnover and is not statistically significant at the 5% level (as represented by the dashed line). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and 2-digit sectors that we do not have data for in every single year. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), ONS *GDP output approach-low-level aggregates* (2016-2021), the *Annual Business Survey* (2021) and the *Business Structure Database* (1997-2022).

Figure E.6: Relative total trade and markups are not correlated

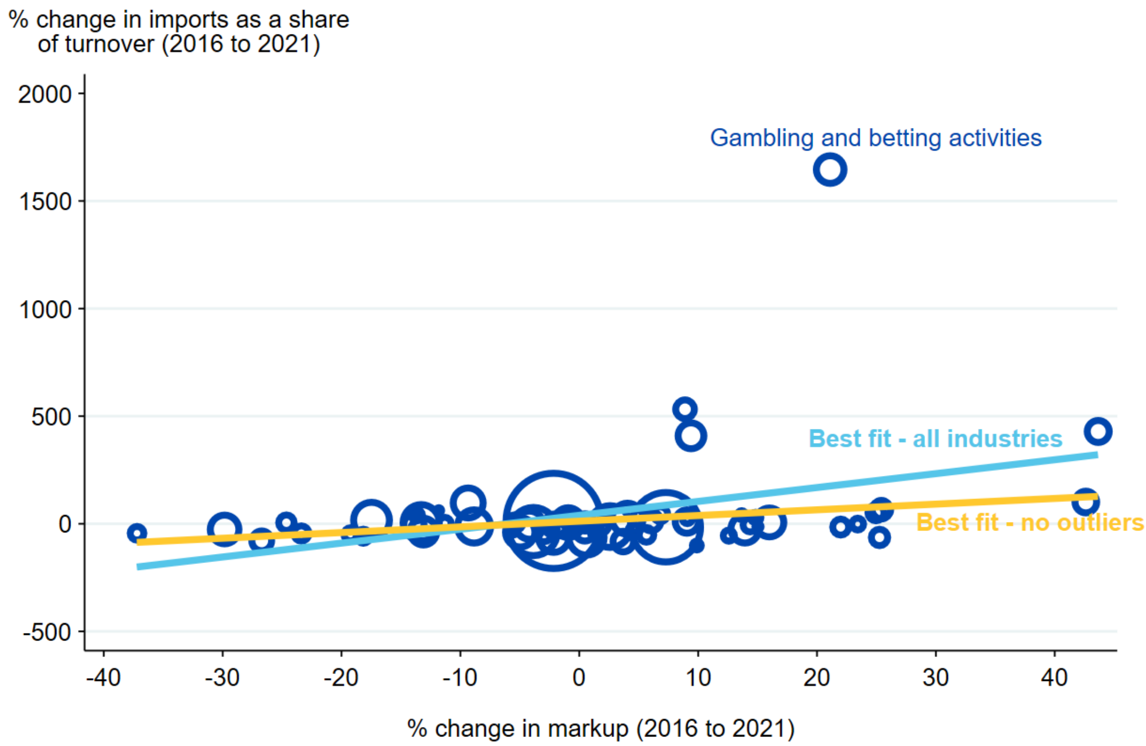
Scatterplot of the average value of total trade relative to gross value added against average markups at the two-digit Standard Industrial Classification level between 2016 and 2021. Data from Annual Respondent Database x (2016-2020), Annual Business Survey (2021), Business Structure Database (2016-2021), ONS GDP Output Approach (2016-2021) and ONS UK Trade in services/goods by industry, country, and service type (2016-2021)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fit weighted by turnover and is not statistically significant at the 5% level (as represented by the dashed line). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and 2-digit sectors that we do not have data for in every single year. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), ONS *GDP output approach low-level aggregates* (2016-2021), the *Annual Business Survey* (2021) and the *Business Structure Database* (1997-2022).

Figure E.7: The percentage change in import expenditure as a share of turnover is positively correlated to the percentage change in markups between 2016 and 2021

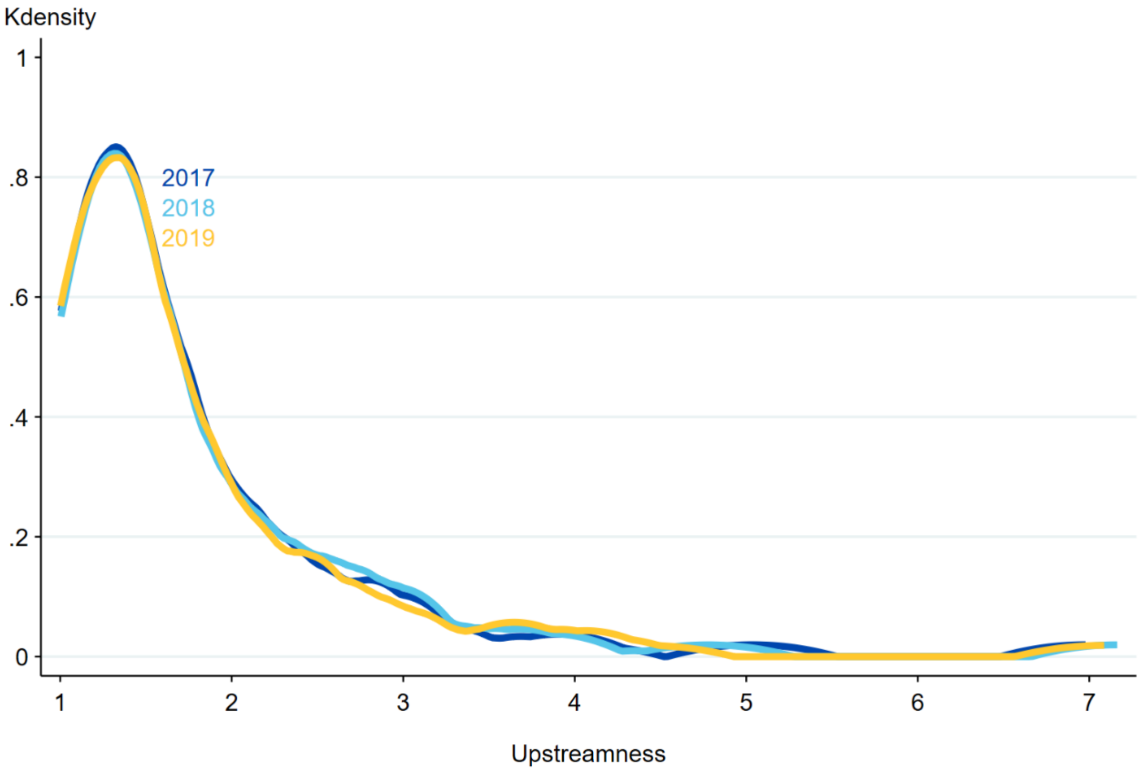
Scatterplot of the percentage change in import expenditure relative to turnover against the percentage change in markups at the two-digit Standard Industrial Classification sector between 2016 and 2021. Data from Annual Respondent Database x (2016-2020), Annual Business Survey (2021), Business Structure Database (2016-2021) and ONS UK Trade in services/goods by industry, country, and service type (2016-2021)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fits weighted by turnover and statistically significant at the 5% level. Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and 2-digit sectors that we do not have data for in every single year. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), *ONS UK trade in services/ goods by industry, country and service type, imports* (2016-2021) and the *Business Structure Database* (1997-2022).

Figure E.8: The distribution of the average distance from consumers has remained broadly consistent between 2017 and 2019

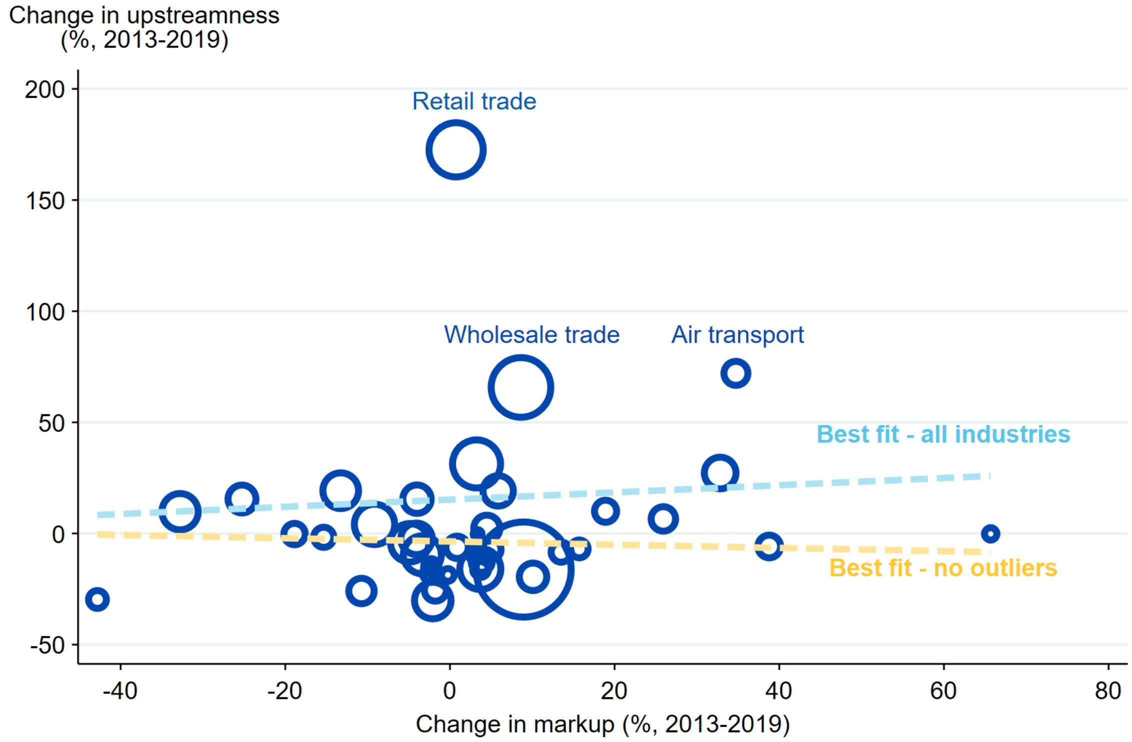
Kdensity plot of upstreamness in each year between 2017 and 2019. Data from Office for National Statistics input-output tables (2017 to 2019)



Upstreamness measures the number of production stages from final use. Source: *Office for National Statistics input-output tables* (2013-2019).

Figure E.9: The percentage change in distance from final consumers is uncorrelated with the percentage change in markups

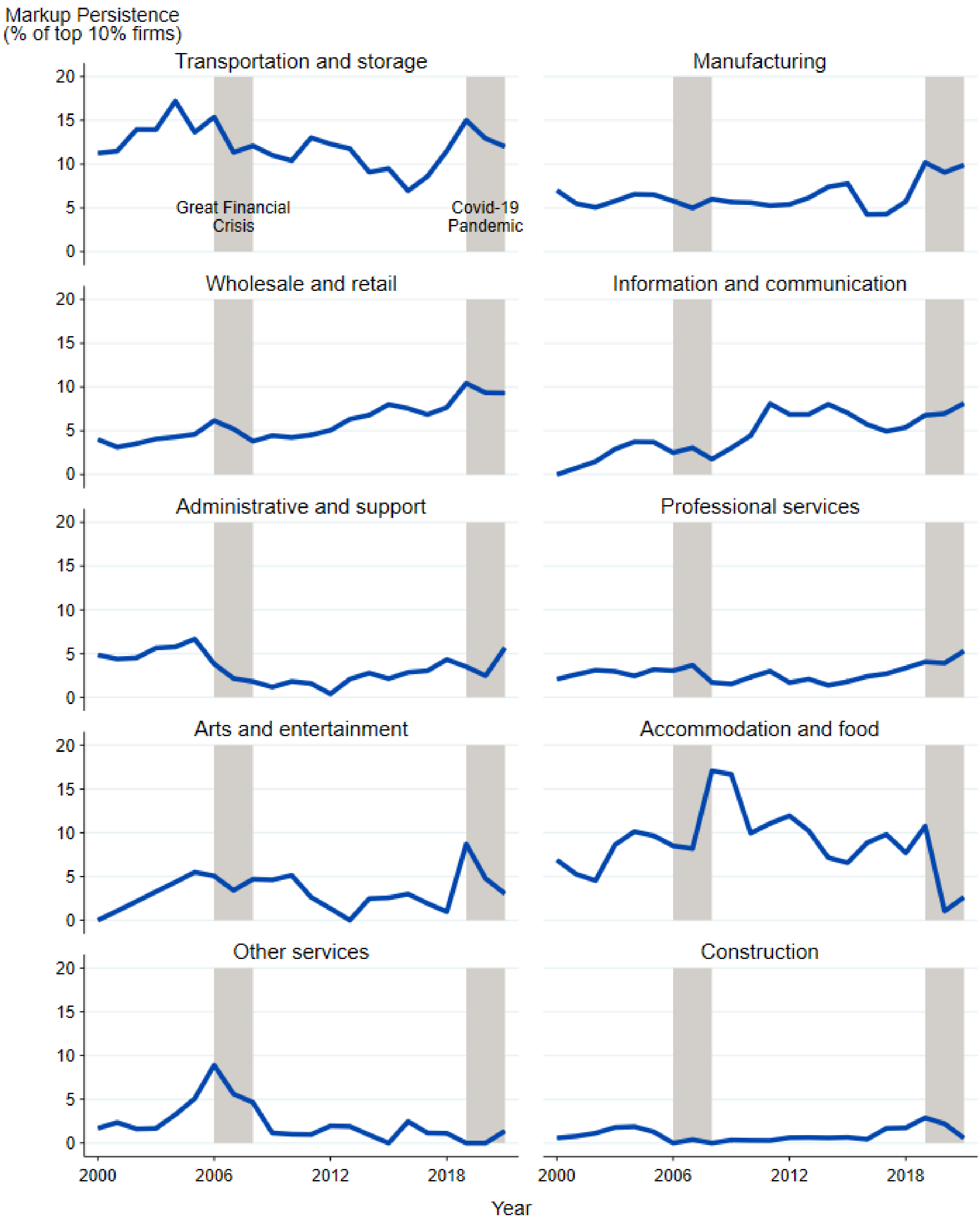
Scatterplot of the percentage change in distance from final consumers (upstreamness) against percentage change in markups. Each bubble represents a two-digit industry (or collection of) and its size denotes the average sectoral share. Data from the Annual Respondents Database X (1997-2020), Annual Business Survey (2021) and input-output tables (2013-2019). GB only



Each data point represents a single (or collection of) 2-digit Standard Industrial Classification (SIC) sector, size represents average sectoral share. Upstreamness measures the number of production stages from final use. Linear fits weighted by sectoral share and not statistically significant at the 5% level (as represented by the dashed lines). Markups are calculated following our baseline approach described in the report. Calculations exclude SIC sectors: A, B, D, E, K, L, O, P, Q, T, U and 2-digit sectors that we do not have data for in every single year. Data from the *Annual Respondents Database X* (1997-2020) and *Annual Business Survey* (2021). Data from *input-output tables* (2013-2019).

Figure E.10: Markup persistence varies by sector

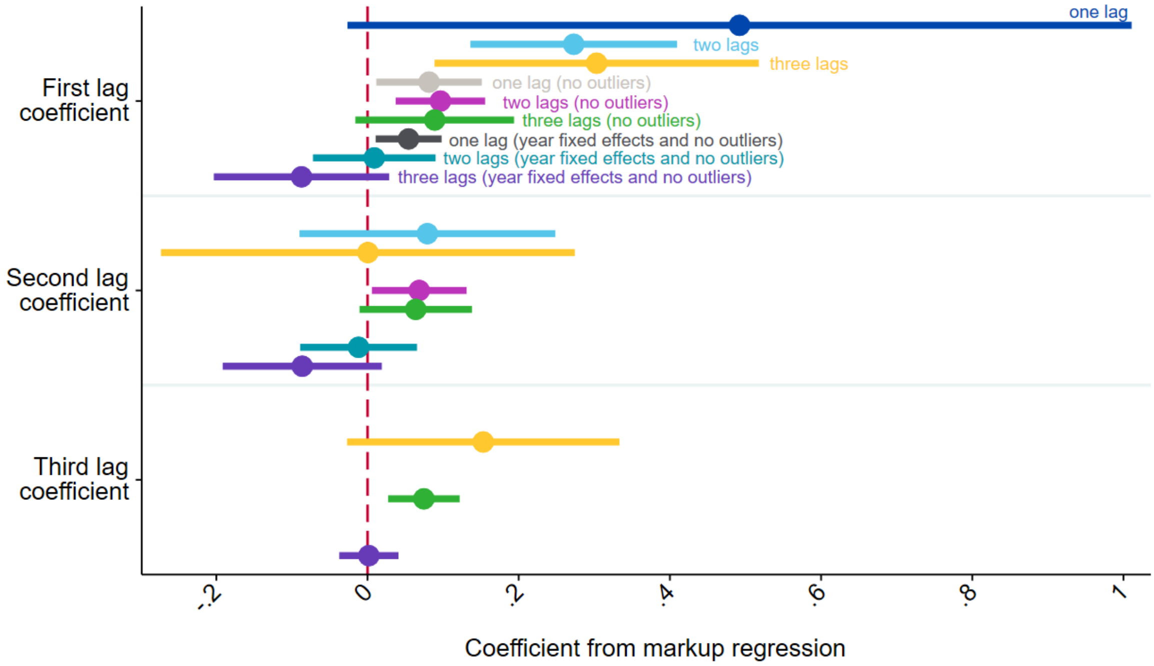
Sectoral persistence of firms at top 10% of markup distribution, from the Business Structure Database, 1997-2022



Persistence defined as percentage of firms (reporting units) in the top 10% of markup distribution that were in the top 10% also in the previous three years. Persistence calculated in each Standard Industrial Classification (SIC) industry. Calculations exclude SIC sectors: A, B, D, E, K, L, O, P, Q, T, U. Industries are ranked by highest persistence in 2021. Data from the *Annual Respondents Database X* (1997-2020) and the *Annual Business Survey* (2021).

Figure E.11: The direction and magnitude of the relationship between markup and its lags depend on the model specification

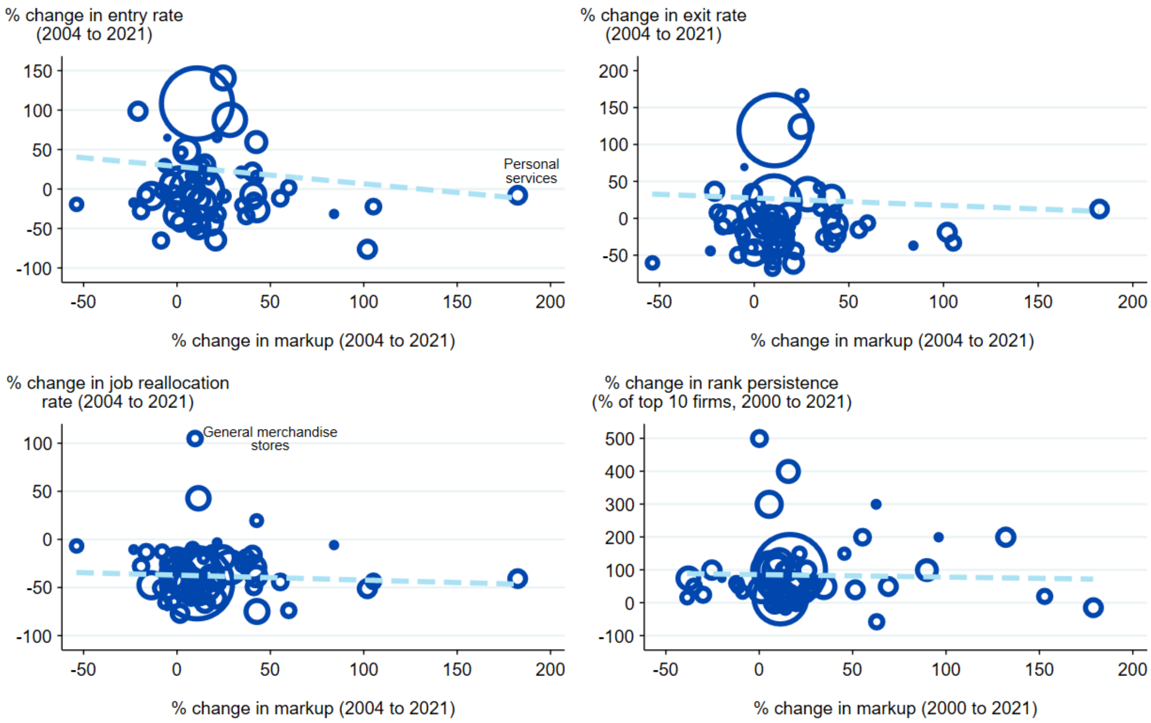
Coefficient plot from a set of regressions of markups on its lags. Data from the Annual Respondents Database X (1997-2020), the Annual Business Survey (2021) and the Business Structure Database (1997-2021)



Each point represents a coefficient from a set of regressions of markups on its lags. The different specifications are colouredand labeled accordingly. Markups estimated using our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data form the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), the *Business Structure Database* (1997-2021).

Figure E.12: Percentage changes in business dynamism measures are uncorrelated with percentage changes in markups

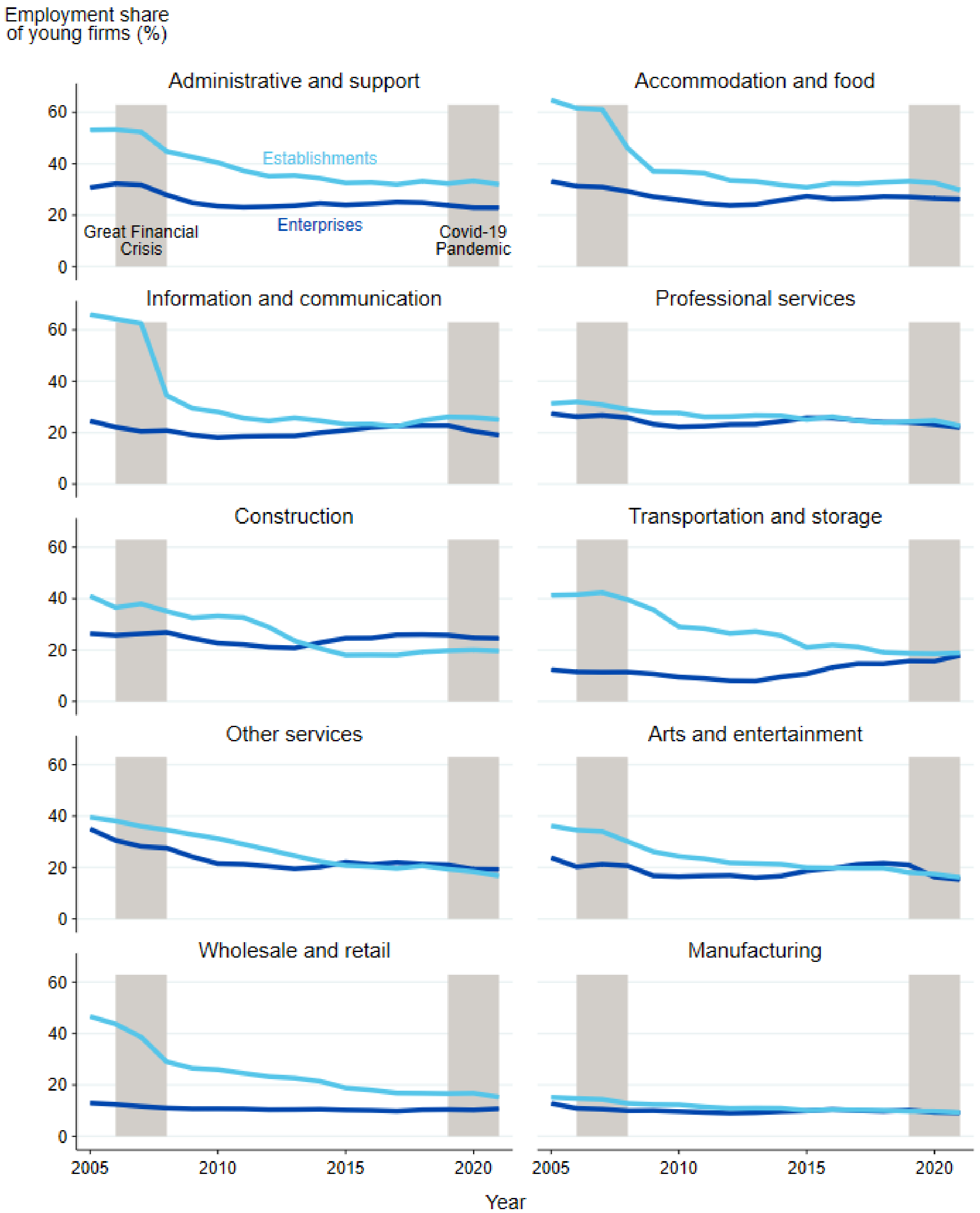
Standard Industrial Classification (SIC) industry level scatterplot between four business dynamism measures and markups, 2004-2021, from the Annual Respondents Database X (1997-2020), the Annual Business Survey (2021) and Longitudinal Business Database (2004-2021)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Lines of best fit weighted by turnover and not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U and 2-digit sectors that we do not have data for in every single year. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X (1997-2020)*, the *Annual Business Survey (2021)*, the *Business Structure Database (1997-2021)* and the *Longitudinal Business Database (2004-2021)*.

Figure E.13: Across sectors, the employment share of young enterprises has fallen while the employment share of young enterprises stayed constant

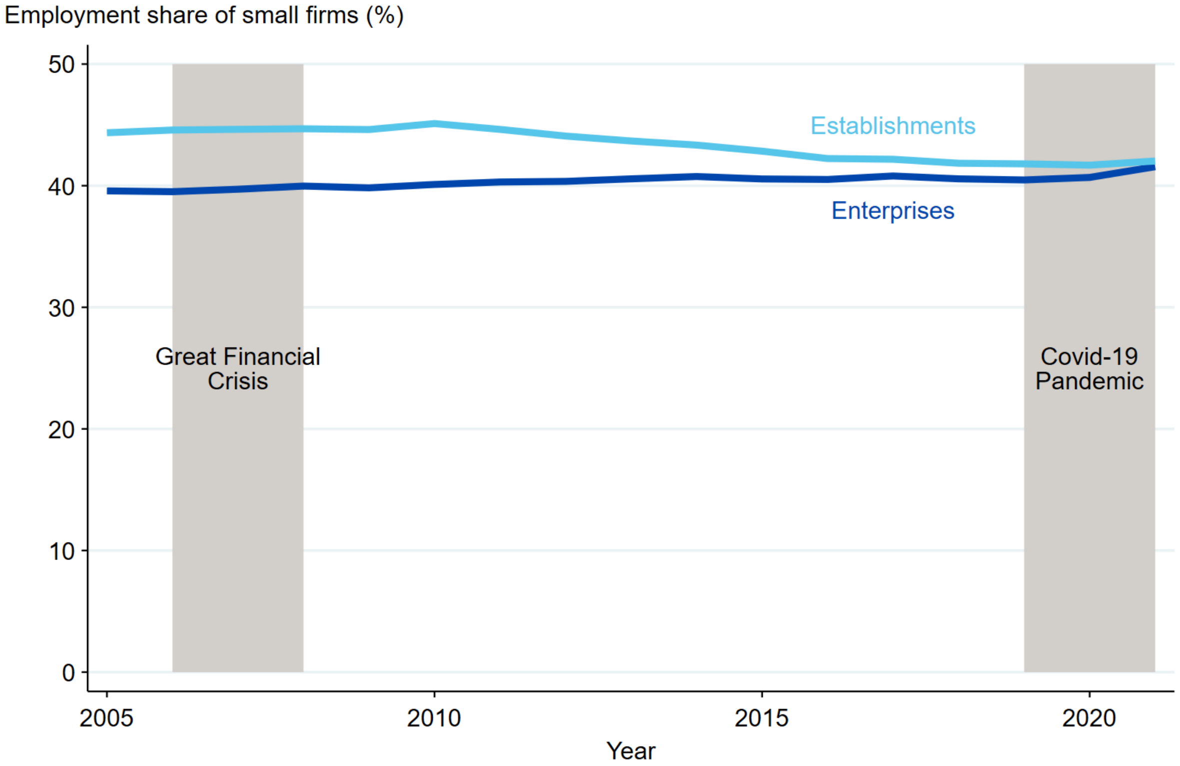
Employment share of establishments and enterprises less than 5 years old by Standard Industrial Classification (SIC) industry. Age of establishments and enterprises estimated using the year of first appearance on the Longitudinal Business Database. Data from the Longitudinal Business Database, 2005-2021. UK



Employment share of enterprises and local units younger than 5 years old by Standard Industrial Classification (SIC) industry. Age of establishments and enterprises estimated using the year of first appearance on the *Longitudinal Business Database*. Calculations exclude SIC sectors: A, B, D, E, K, L, O, P, Q, T, U. Industries are ranked by the highest employment share of establishments in 2021. Data from the *Longitudinal Business Database* (2005-2021).

Figure E.14: The employment share of small establishments has fallen slightly while the employment share of small enterprises has remained constant

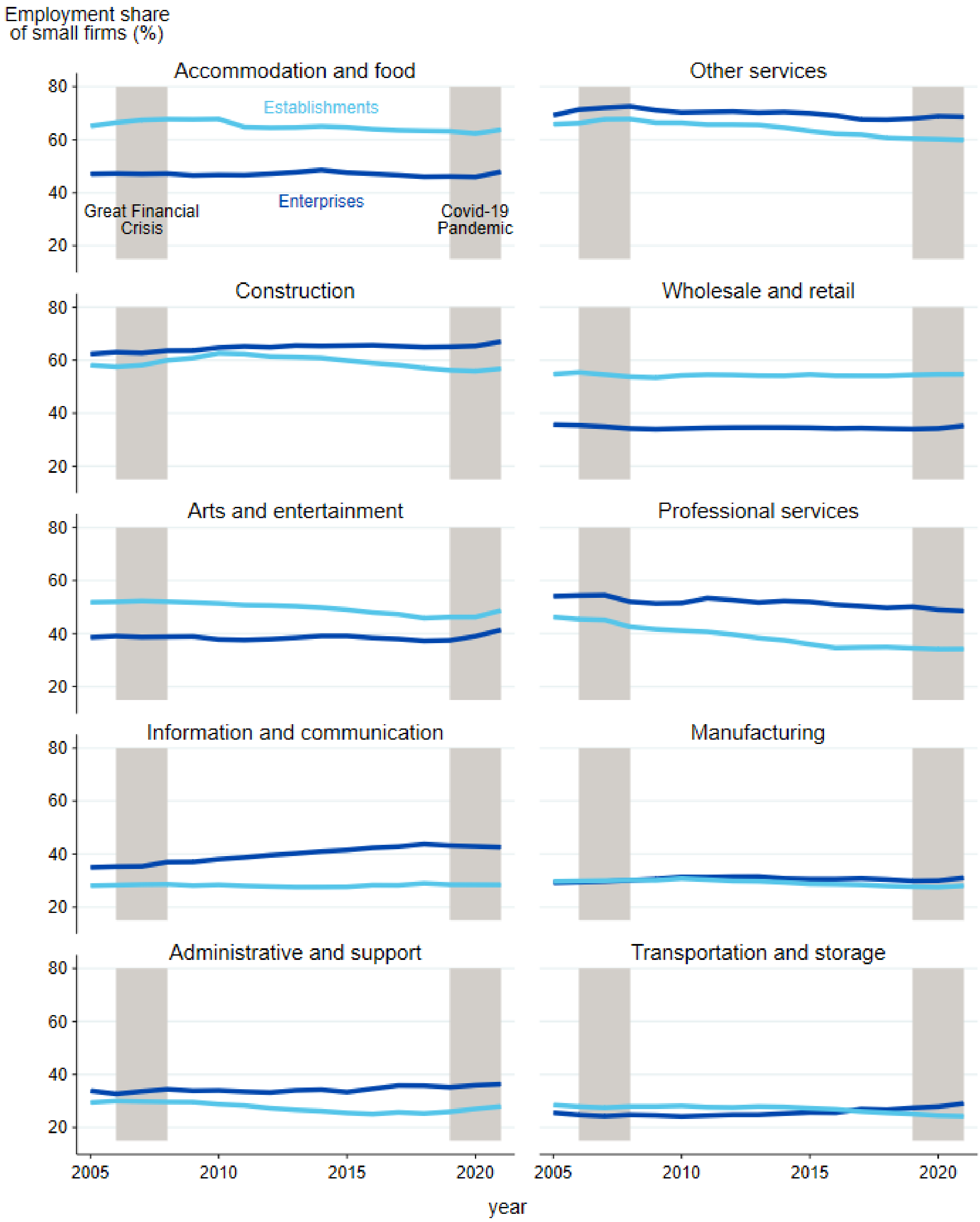
Whole-economy employment share of enterprises and establishments with employment under 50, data from the Longitudinal Business Database, 2005-2021. UK



Employment share of enterprises and local units with employment less than 50. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2005-2021).

Figure E.15: In most sectors, the employment share of small establishment and enterprises has remained broadly constant

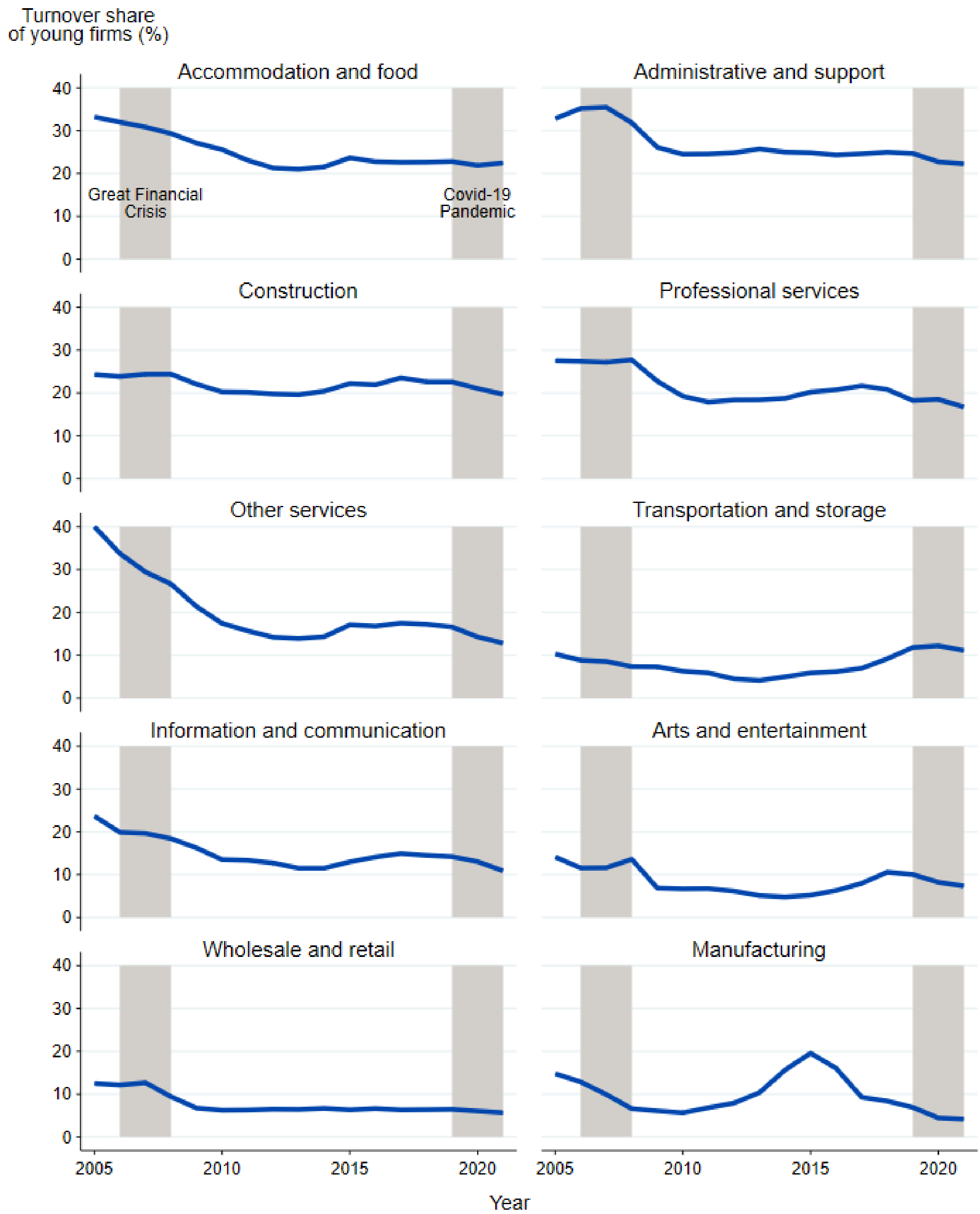
Employment share of establishments and enterprises with employment under 50 by Standard Industrial Classification (SIC) industry, 2005 – 2021, from the Longitudinal Business Database. UK



Employment share of enterprises and local units with employment less than 50 by Standard Industrial Classification (SIC) industry. Calculations exclude SIC sectors: A, B, D, E, K, L, O, P, Q, T, U. Industries ordered by highest employment share of establishments in 2021. Data from the *Longitudinal Business Database* (2005-2021)

Figure E.16: In most sectors, the turnover share of young enterprises has fallen

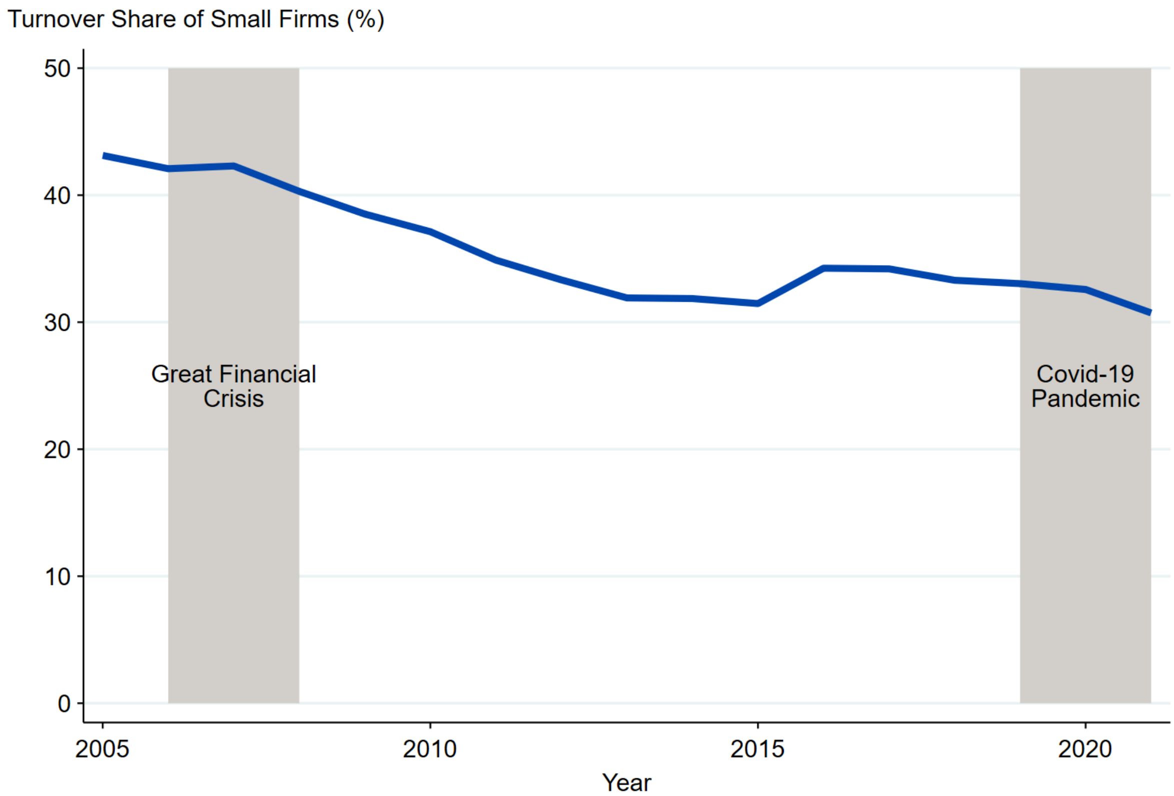
Turnover share of enterprises less than 5 years old. Age of enterprises estimated using the year of first appearance on the Longitudinal Business Database. Data from the Longitudinal Business Database, 2005-2021. UK



Turnover share of enterprises younger than 5 years old by Standard Industrial Classification (SIC) industry. Age of enterprises estimated using the year of first appearance on the *Longitudinal Business Database*. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Industries ranked by highest turnover share in 2021. Data from the *Longitudinal Business Database* (2005-2021).

Figure E.17: The turnover share of small enterprises has fallen over time

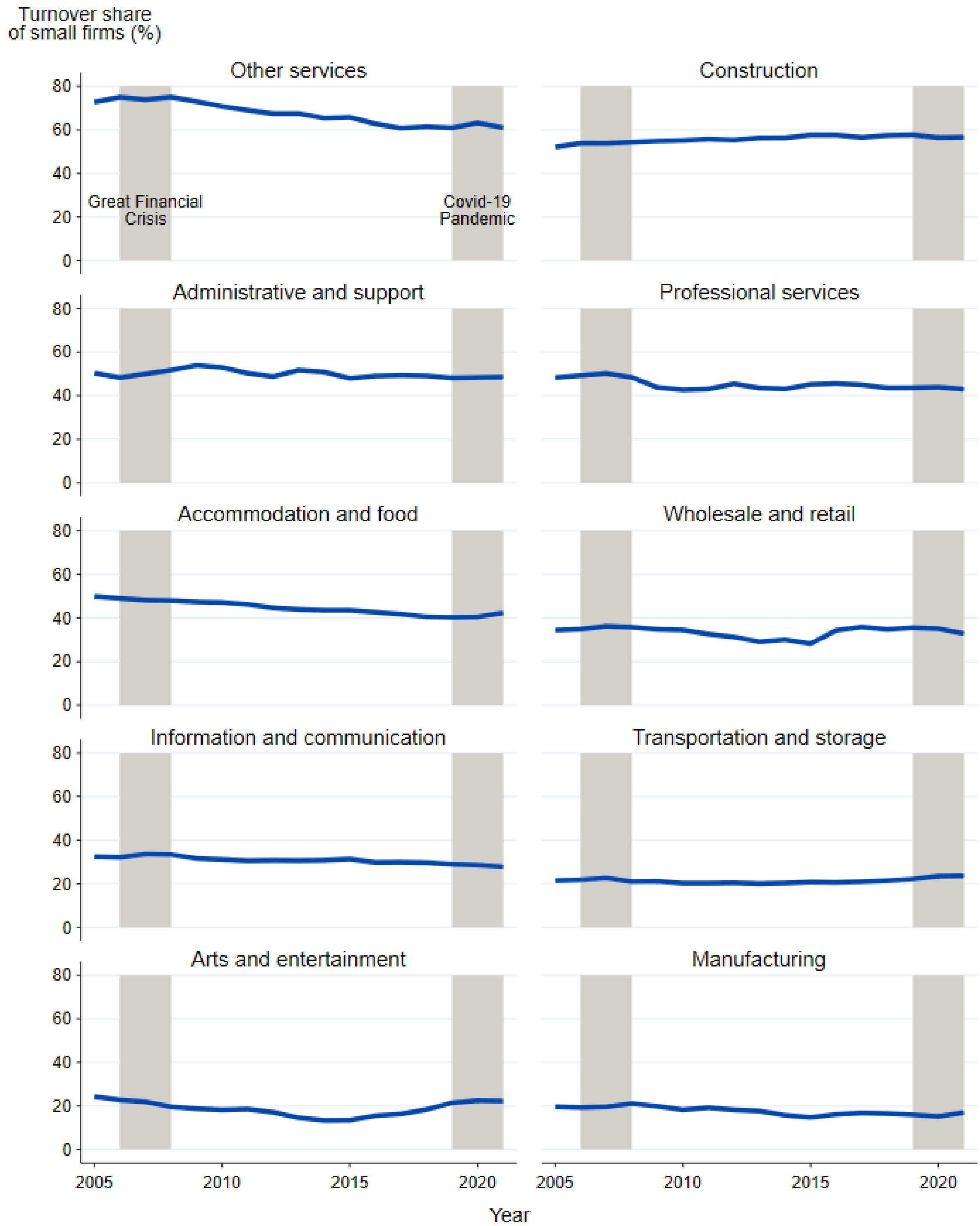
Whole-economy turnover share of enterprises with employment under 50, data from the Longitudinal Business Database, 2005-2021. UK



Turnover share of enterprises with employment under 50. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2005-2021).

Figure E.18: The economy-wide decline in the turnover share of small firms is driven by a few sectors, among which other services and food and accommodation

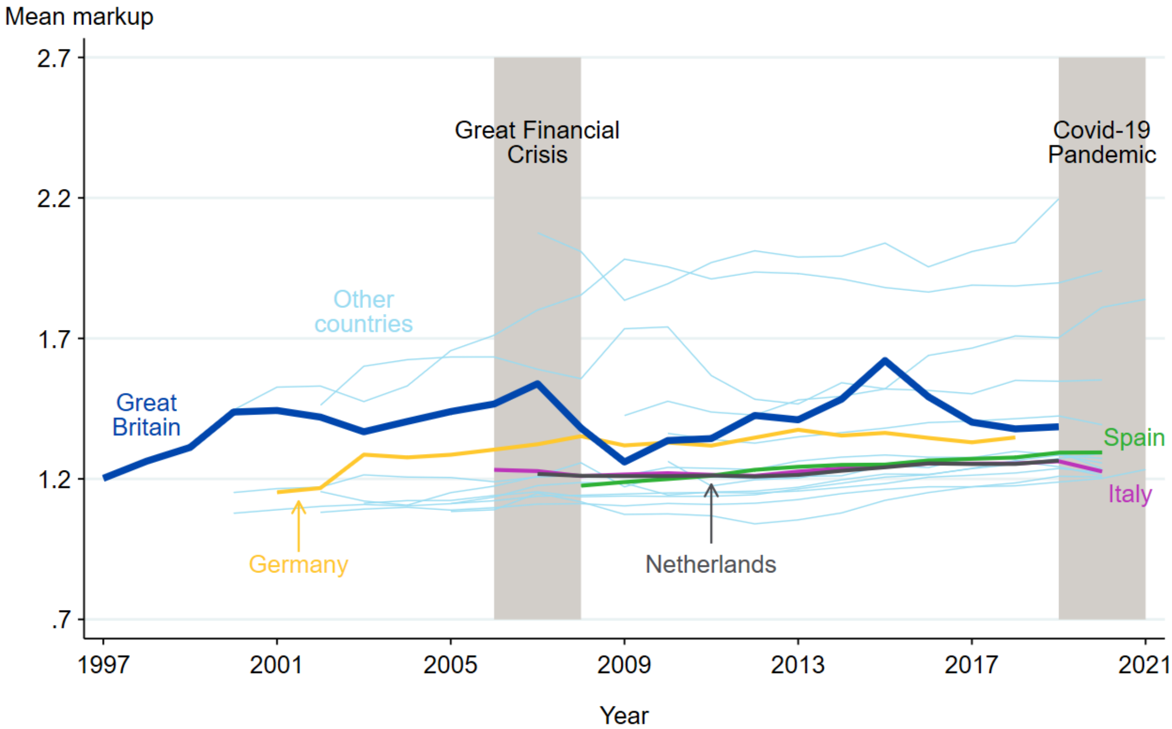
Sectoral turnover share of enterprises with employment under 50, data from the Longitudinal Business Database, 2005-2021. UK



Employment share of enterprises and local units with employment less than 50. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Longitudinal Business Database* (2005-2021).

Figure E.19: GB markup levels are slightly higher than European peers

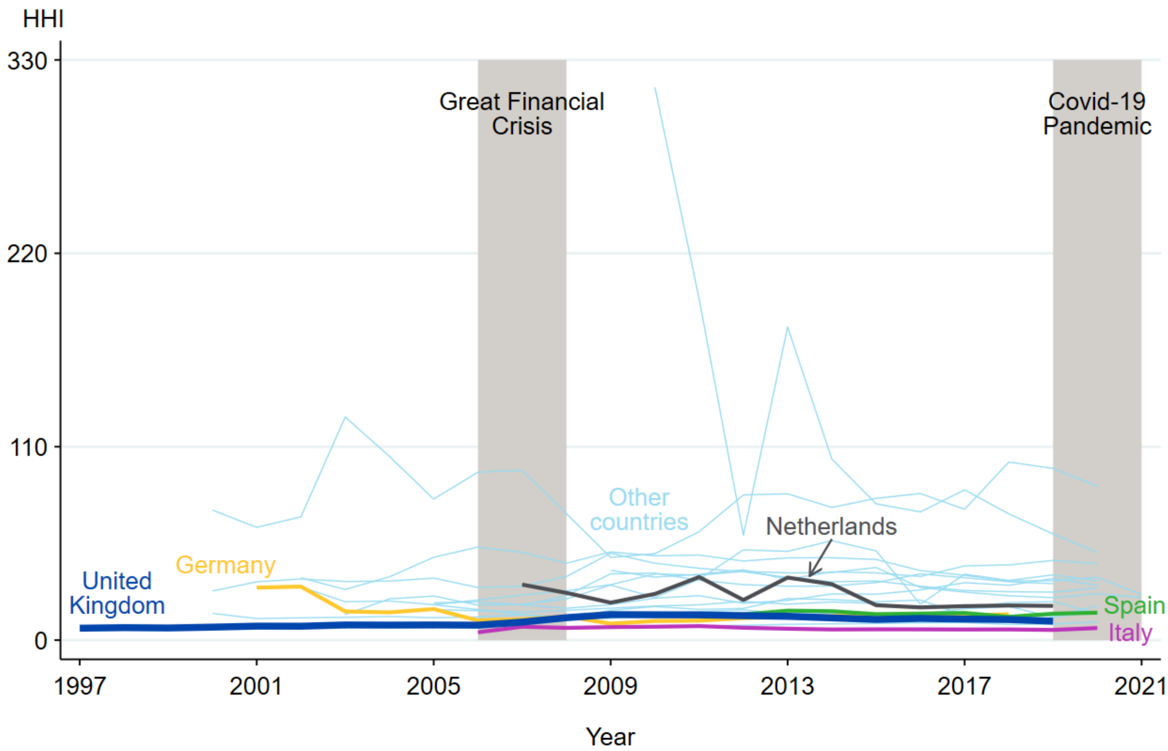
Economy-wide average markup estimates, ordinary least squares estimation of a translog production function, data from the Competitiveness Research Network (CompNet), 1997-2021



Markup estimated using production function approach. Ordinary Least Square estimation of a translog production function, with materials as flexible input. Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Figure E.20: Concentration levels in the UK are similar to other European countries

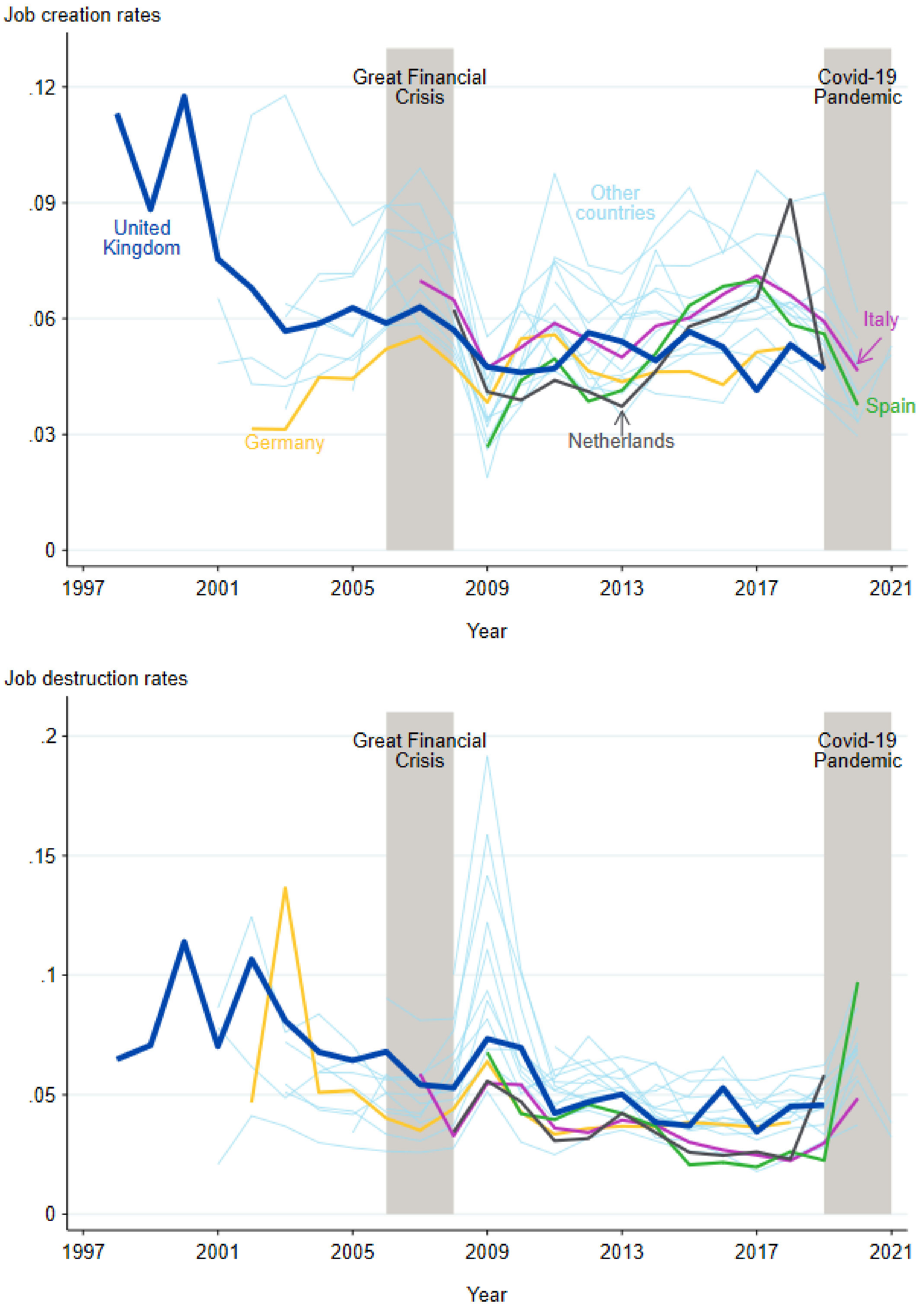
Economy wide mean Herfindahl-Hirschman Index, data from the Competitiveness Research Network (CompNet), 1997-2021



Estimates of Herfindahl-Hirschman Index (HHI). Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Figure E.21: Job creation and destruction rates in the UK are similar to those in other European countries

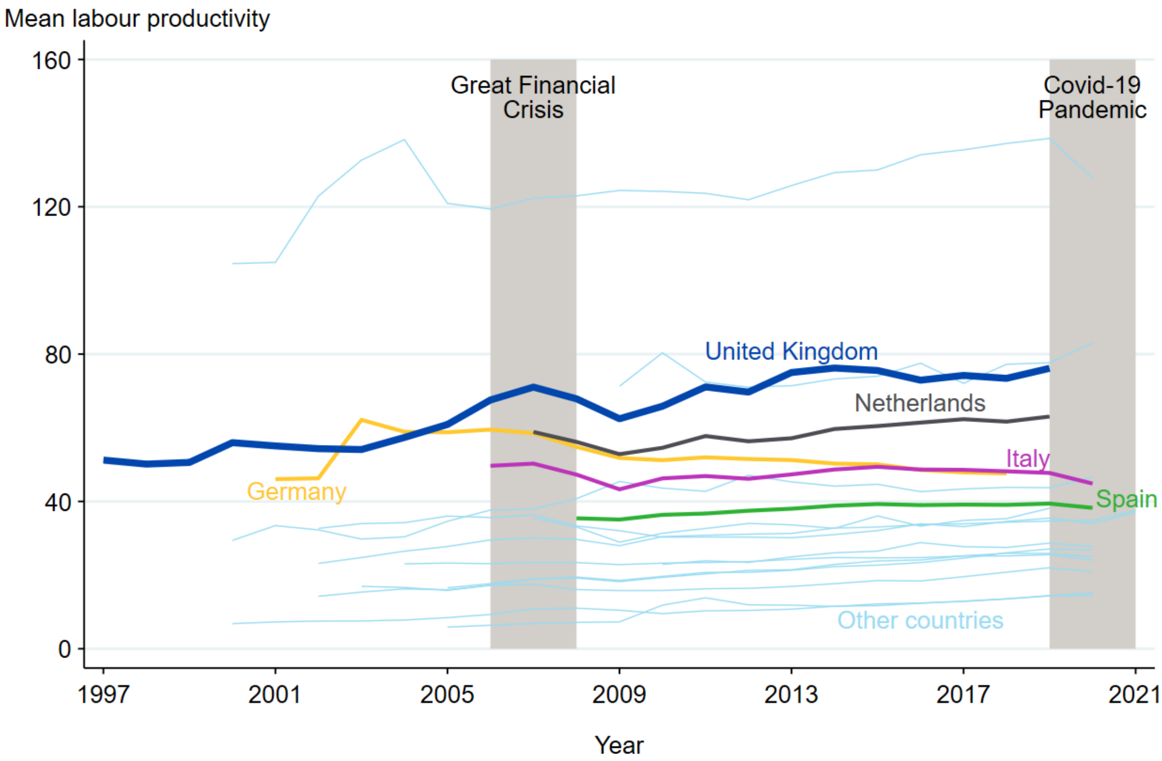
Economy wide estimates of job creation and job destruction rates, data from the Competitiveness Research Network (CompNet), 1997-2021. UK



Estimates of job creation and destruction rates. Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Figure E.22: UK mean labour productivity is higher than European peers

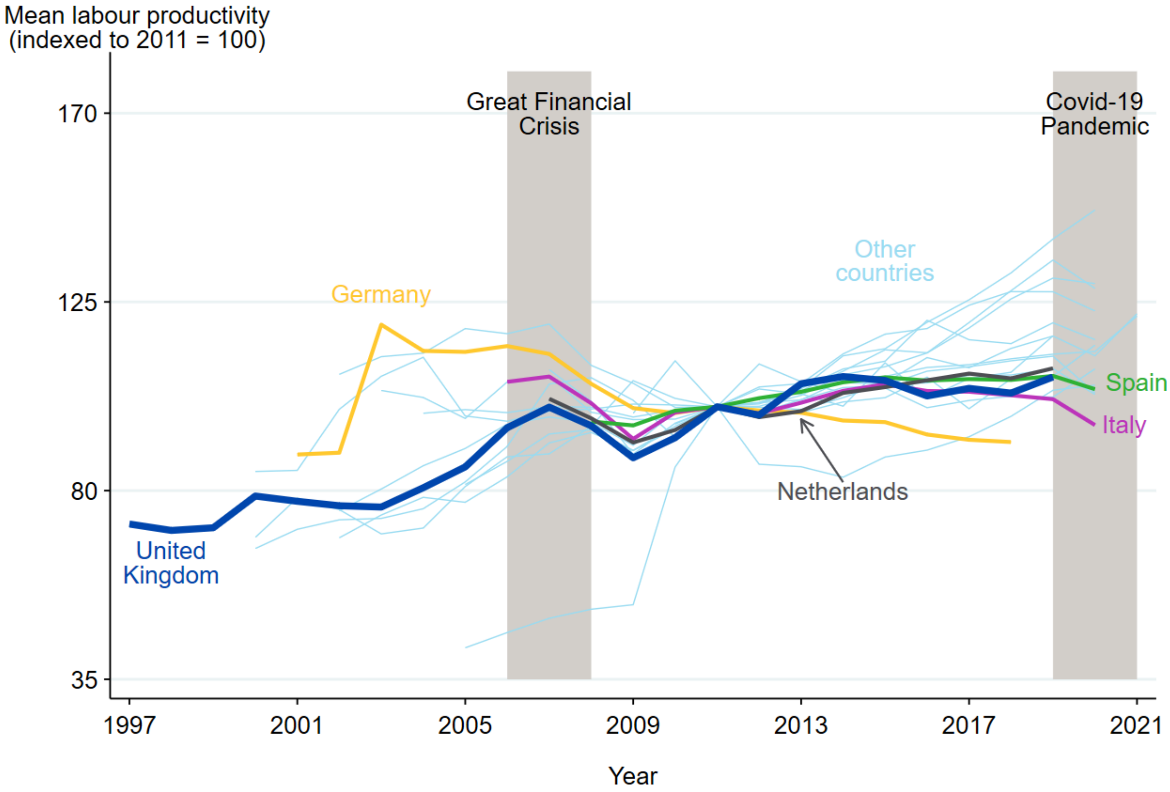
Economy wide estimates of mean labour productivity, data from the Competitiveness Research Network (CompNet), 1997-2021. UK



Estimates of mean labour productivity. Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Figure E.23: UK mean labour productivity increased at a comparable rate to other European nations

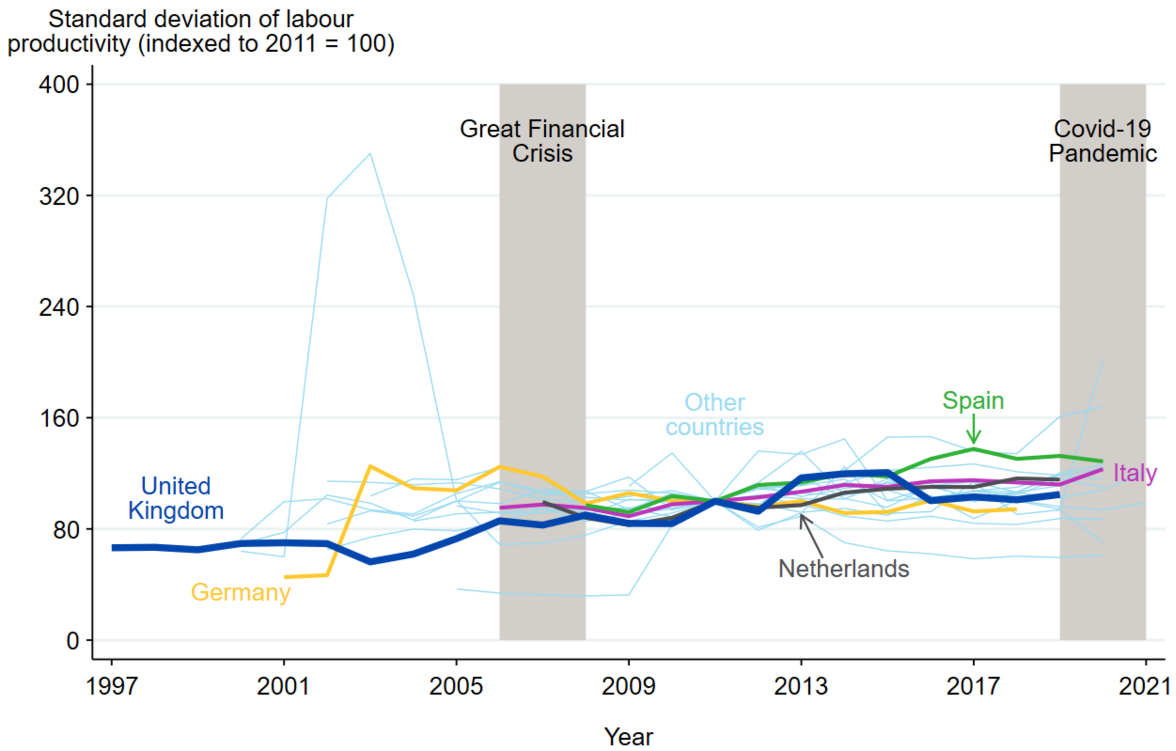
Economy wide estimates of mean labour productivity, data from the Competitiveness Research Network (CompNet), 1997-2021. UK



Estimates of mean labour productivity. Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Figure E.24: UK labour productivity volatility growth exceeded European peers in the early to mid-2010s, before falling to more comparable levels

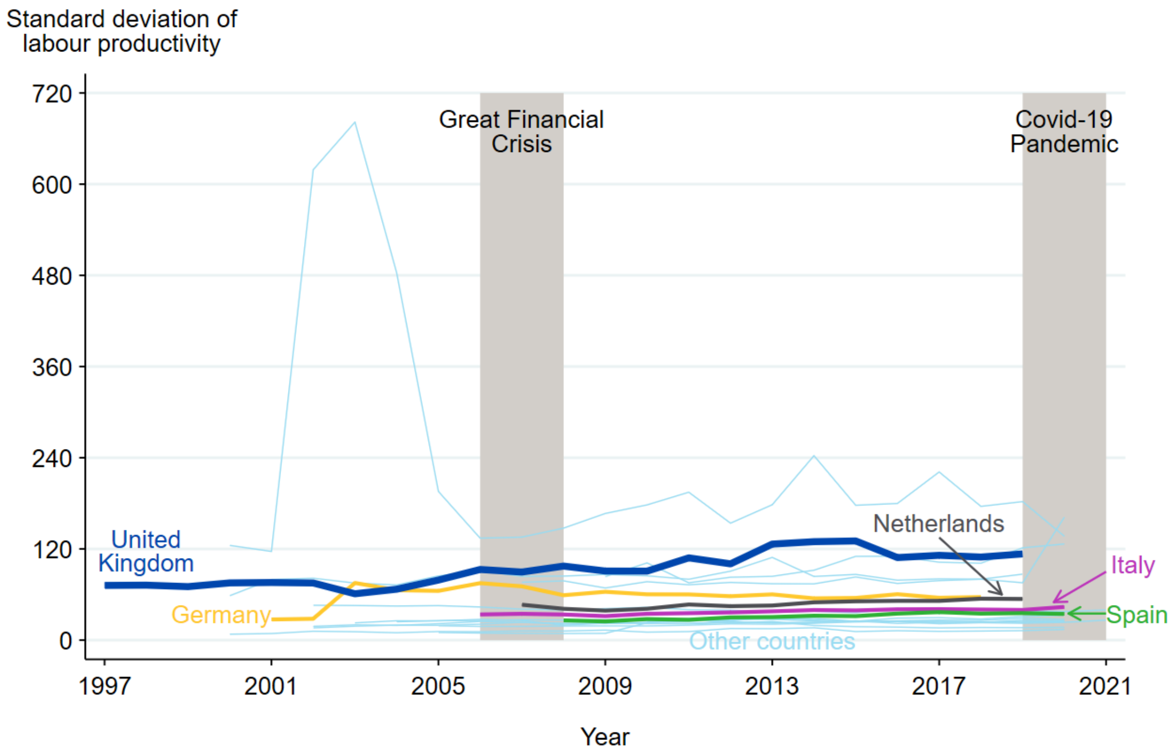
Standard deviation of economy wide estimates of labour productivity, data from the Competitiveness Research Network (CompNet), 1997-2021. UK



Estimates of the standard deviation of labour productivity. Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Figure E.25: UK labour productivity levels are more volatile than other European nations

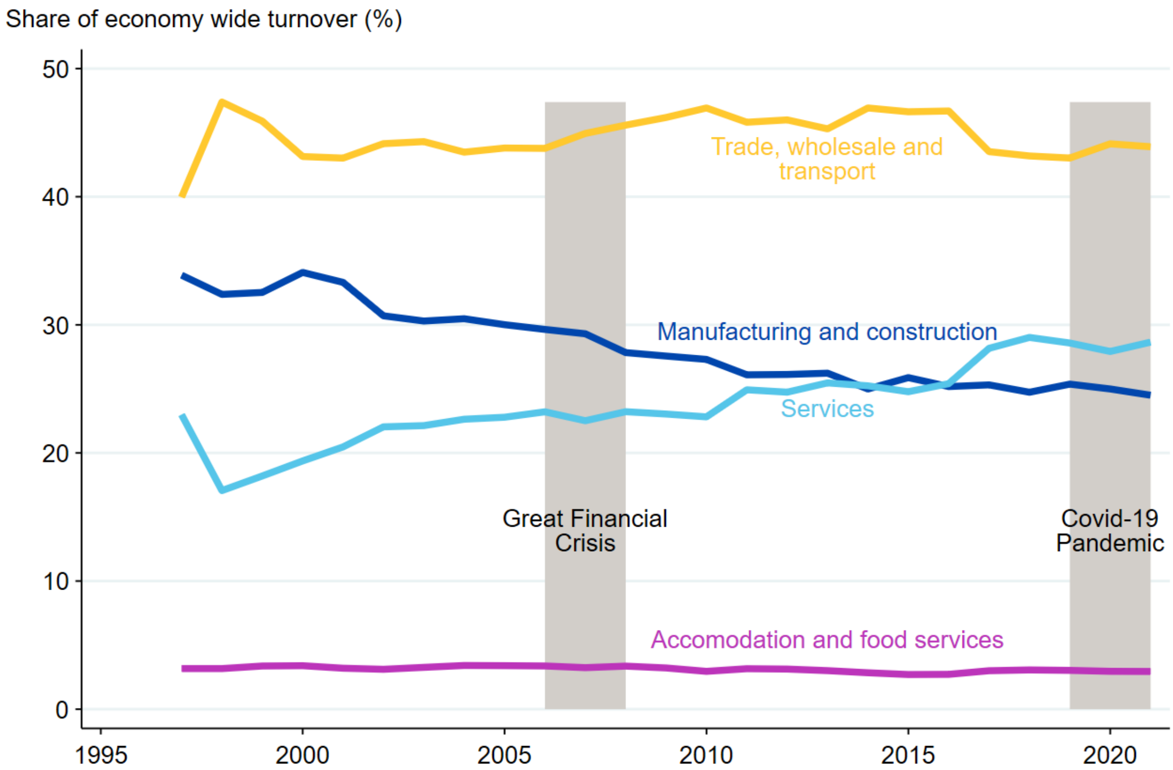
Standard deviation of economy wide estimates of labour productivity, data from the Competitiveness Research Network (CompNet), 1997-2021. UK



Estimates of the standard deviation of labour productivity. Other countries include: Belgium, Croatia, Czech Republic, Hungary, Latvia Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland. Denmark, Finland, France and Sweden excluded. Calculations include statistical classification of economic activities in the European Community (NACE) sectors: C, F, G, H, I, J, L, M, N. Data from the *Competitiveness Research Network (CompNet)* 1997-2021.

Figure E.26: The services share of the UK economy has risen since 1997, while the manufacturing share has declined

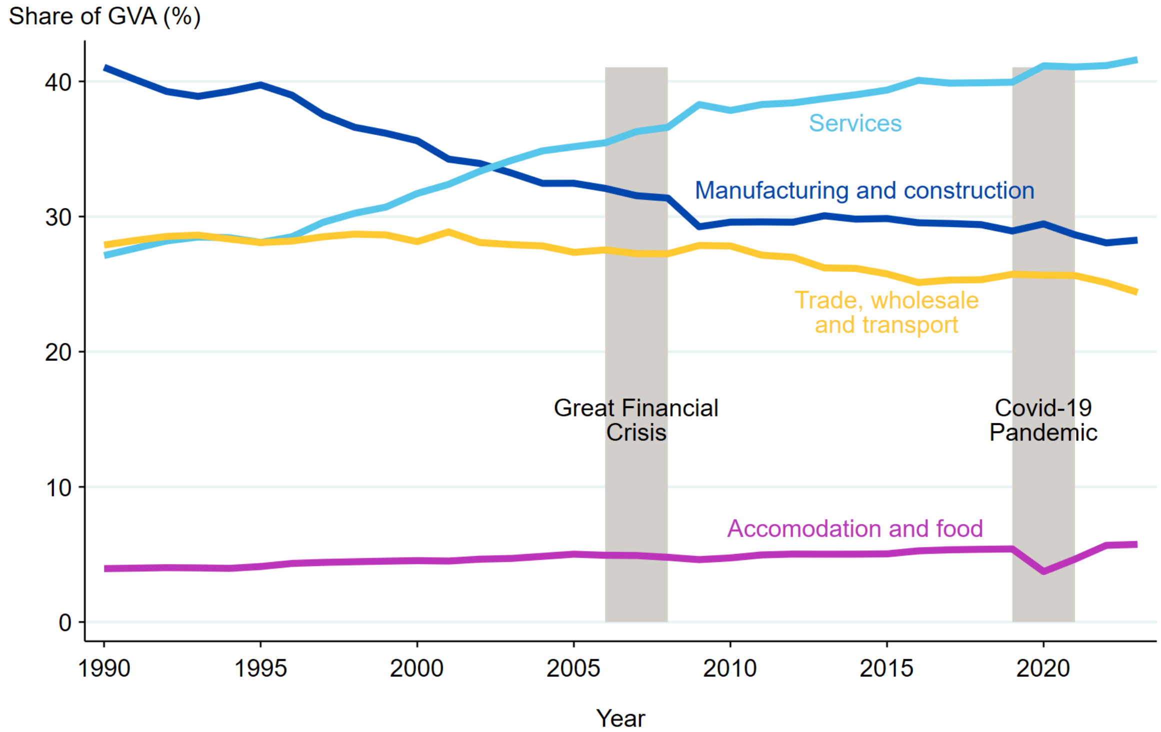
Broad sector share of economy wide turnover in constant prices, from the Business Structure Database, 1997-2021. UK



Analysis excludes Standard Industrial Classification sectors: A, B, D, E, K, L, O, P, Q, T and U. Source: the *Business Structure Database (1997 to 2021)*

Figure E.27: The services share of the UK economy has risen since 1990, while the manufacturing share has declined

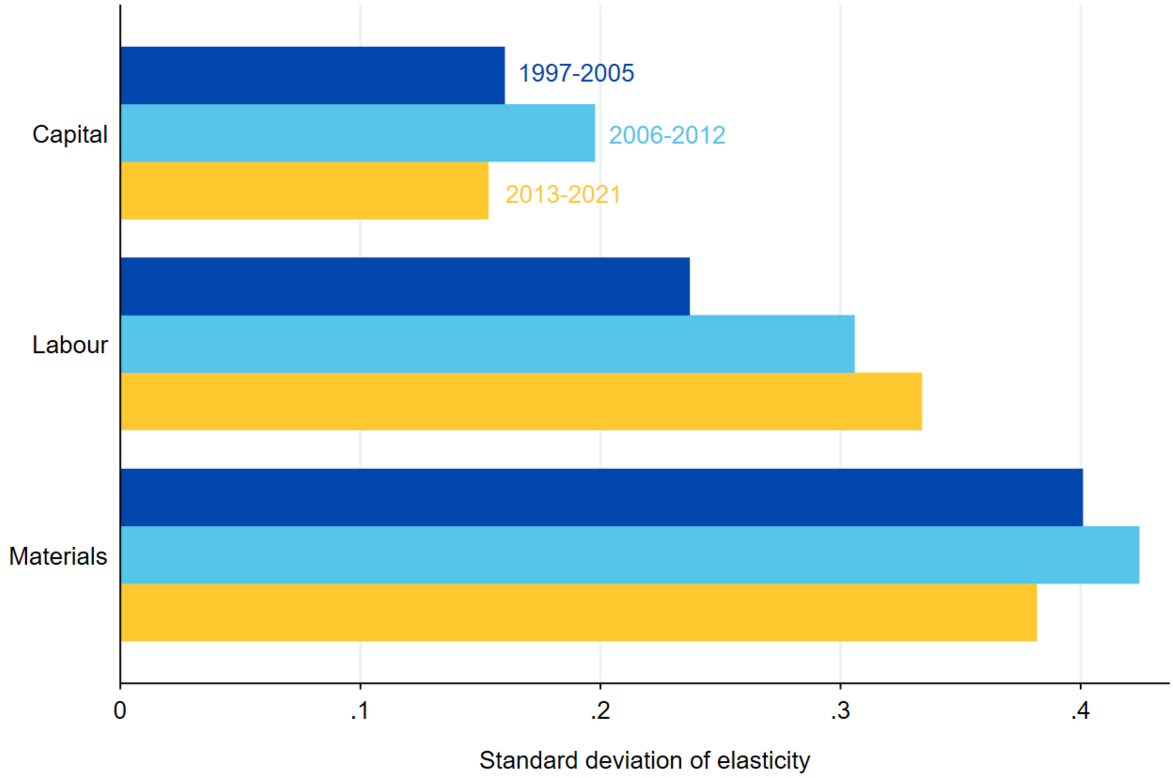
Broad sector share of Gross Value Added (GVA) in current prices, from ONS GDP Output Approach dataset, UK, 1990-2023



Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Source: *Office for National Statistics GDP output approach – low-level aggregates* (1990-2023)

Figure E.28: The variance in the additional output yielded by employing an extra unit of labour has increased

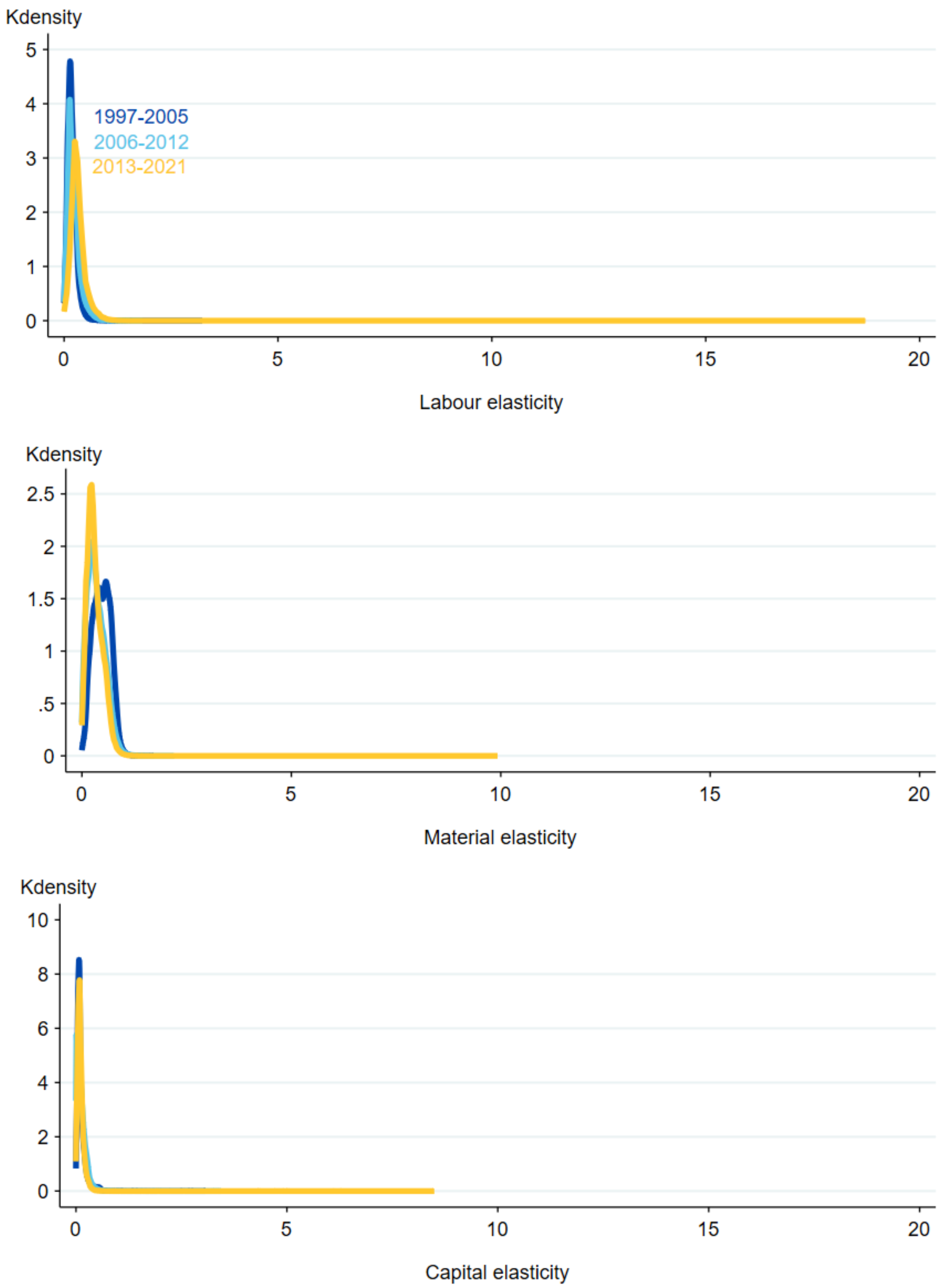
Standard deviation of mean of capital, labour and materials elasticities. The elasticities result from an Ordinary Least Square estimation of a translog production function, as per our baseline approach to markup estimation. Data from Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey (ABS) 2021. GB only



The elasticities result from an Ordinary Least Square estimation of a translog production function, as per our baseline approach described in the report. The analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Data from the *Annual Respondents Database X* (1997-2020) and the *Annual Business Survey* (2021).

Figure E.29: The distributions of labour and capital elasticities have remained roughly constant

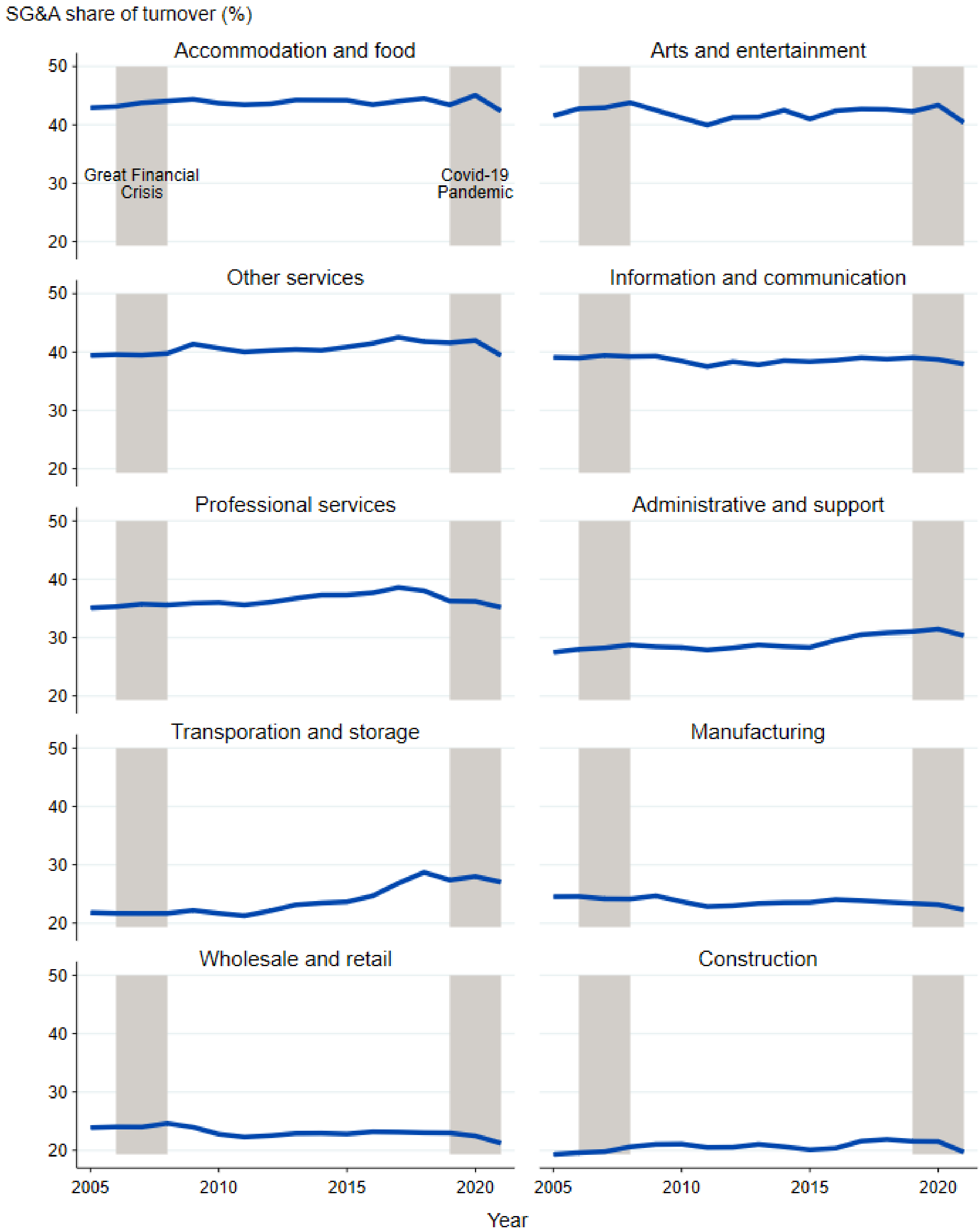
Kdensity plots of capital, labour and materials elasticities. The elasticities result from an Ordinary Least Square estimation of a translog production function, as per our baseline approach to markup estimation. Data from Annual Respondents Database X (ARDx) 1997-2020 and Annual Business Survey (ABS) 2021. GB only



Elasticities result from an Ordinary Least Square estimation of a translog production function, as per our baseline approach described in the report. Data from the *Annual Respondents Database X (1997-2020)* and the *Annual Business Survey (2021)*.

Figure E.30: SG&A expenses as a share of turnover varies by sector

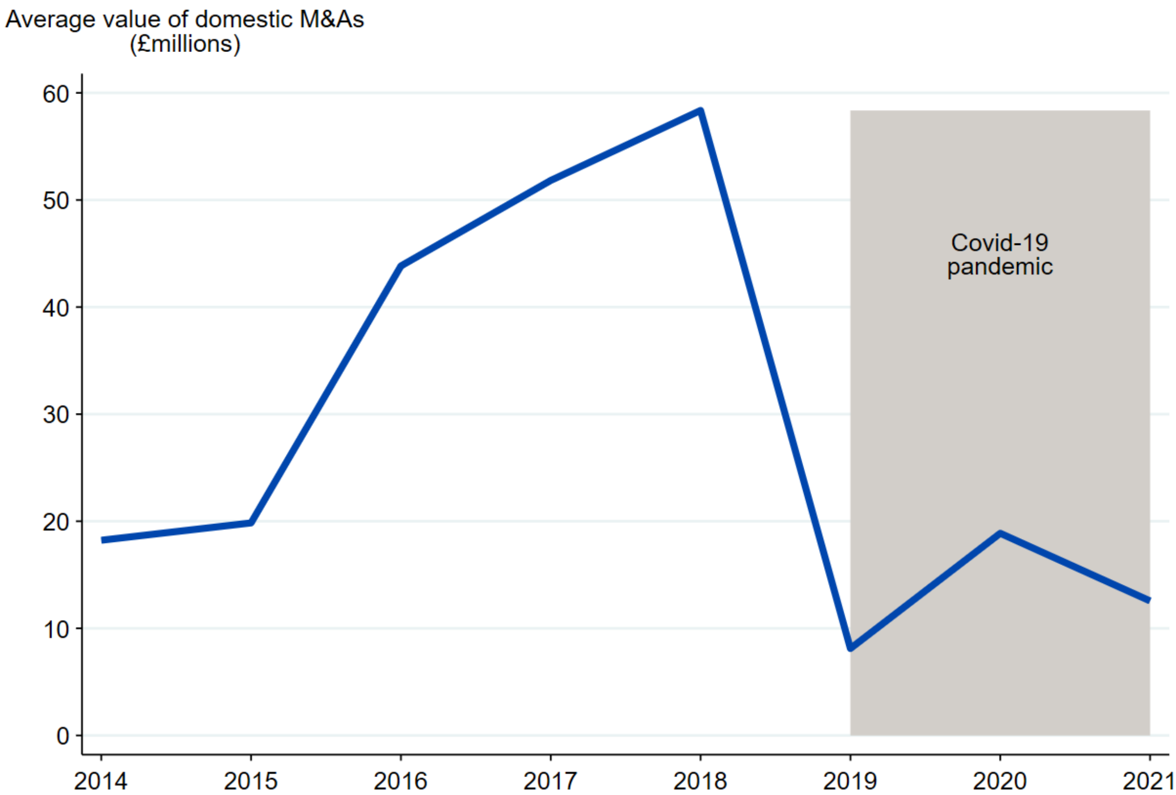
Sectoral SG&A share in turnover as a proxy for fixed costs shares, using data from Bureau van Dijk's FAME, UK, 2005 – 2021



SG&A = gross profit minus earnings before interest, taxes, depreciation and amortization (EBITDA). SG&A share in turnover is computed by dividing SG&A expenses by turnover. Industries are ranked by highest SG&A share in 2021. Data from *Bureau van Dijk's FAME* (2005-2021).

Figure E.31: The mean value of UK mergers and acquisitions fell significantly from 2018 to 2019 and remained low in subsequent years

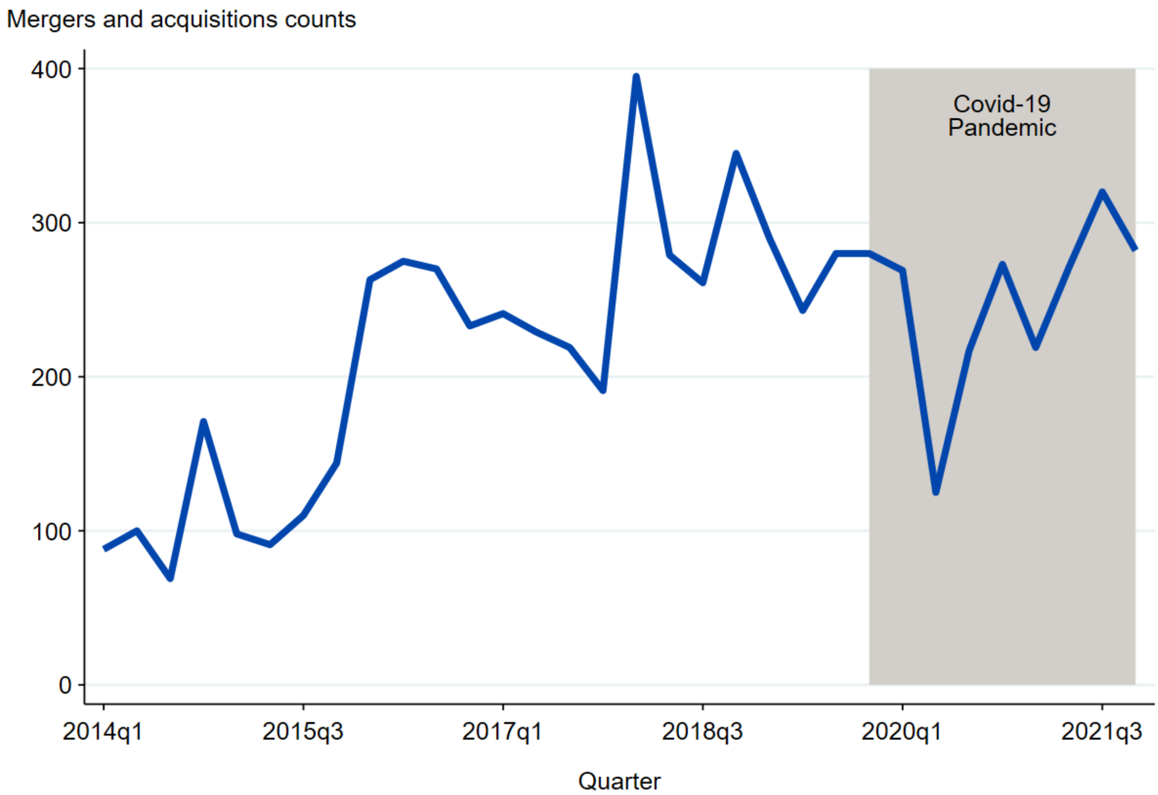
Mean value of domestic UK mergers and acquisitions, data from the Mergers and Acquisitions Survey, 2014 – 2021



Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Mergers and Acquisitions Survey* (2014 Q1-2021 Q4).

Figure E.32: The total count of mergers and acquisitions have risen over the past decade

Counts of UK domestic and outward mergers and acquisitions, data from the Mergers and Acquisitions Survey, 2014 Q1 – 2021 Q4



Quarterly counts of total domestic and outward UK mergers and acquisitions. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Mergers and Acquisitions Survey* (2014 Q1-2021 Q4).

Figure E.33: There is no strong relationship between mergers and acquisitions (M&A) activity and average markups

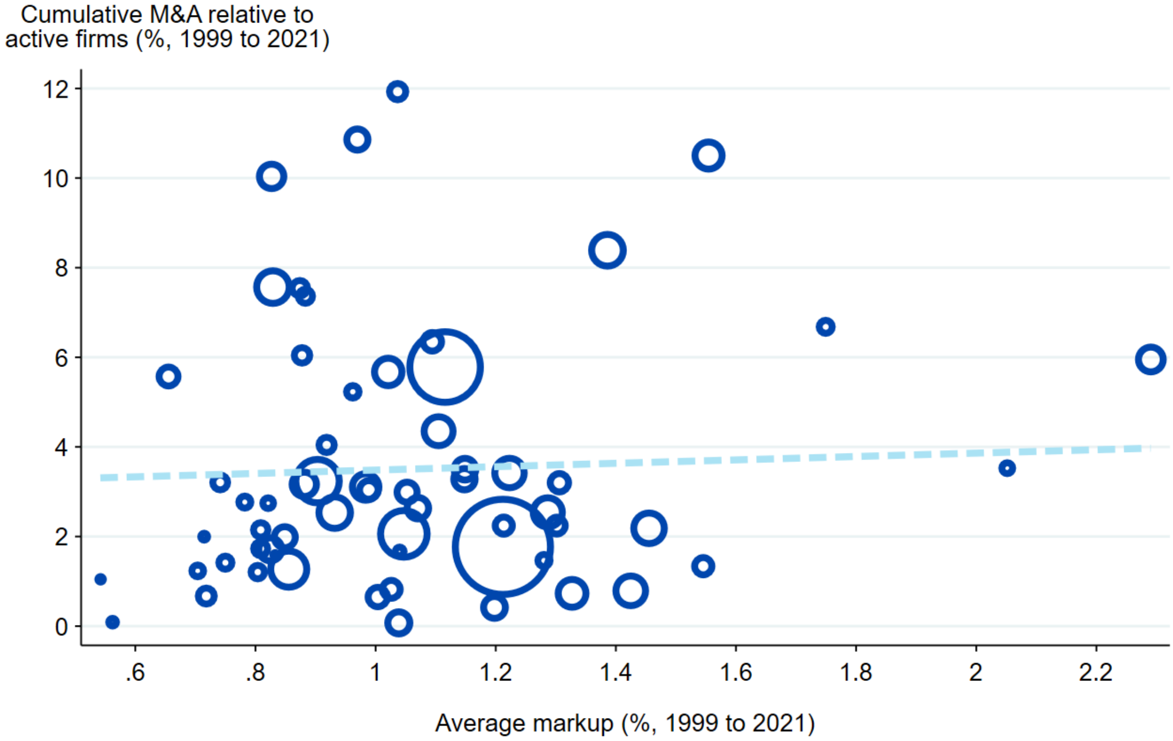
Panel 1: Scatterplot of average markups and average number of mergers and acquisitions relative to the number of active firms by two-digit Standard Industrial Classification between 2014 and 2020, from the Annual Respondents Database X (1997-2020), the Annual Business Survey (2021), Business Structural Database (2014-2020), and ONS Merger and Acquisitions Surveys (2014-2020)

Panel 2: Scatterplot of average markups and average mergers and acquisitions expenditure relative to turnover by two-digit SIC between 2014 and 2020, from the Annual Respondents Database X (1997-2020), the Annual Business Survey (2021), Business Structural Database (2014-2020), and ONS Merger and Acquisitions Surveys (2014-2020)

Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents sectoral average turnover. Lines of best fit weighted by average turnover and not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and the 2-digit industries that do not have data for the entire period. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), the *Business Structure Database* (1997-2022) and the *ONS Merger and Acquisitions Survey* (2014-2020).

Figure E.34: There is no strong relationship between mergers and acquisition (M&A) activity and average markups

Scatterplot of average markup and cumulative M&A (local units to enterprises) as a percentage of average active firms between 1999 and 2021 at a two-digit Standard Industrial Classification (SIC) level, from the Annual Respondents Database x (1997-2020), the Annual Business Survey (2021) and the Longitudinal Business Database (1997-2021)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents sectoral average turnover. Line of best fit weighted by average turnover, not statistically significant at the 5% level (as represented by the dashed line). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and the 2-digit industries that do not have data for the entire period. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), and the *Longitudinal Business Database* (1997-2021).

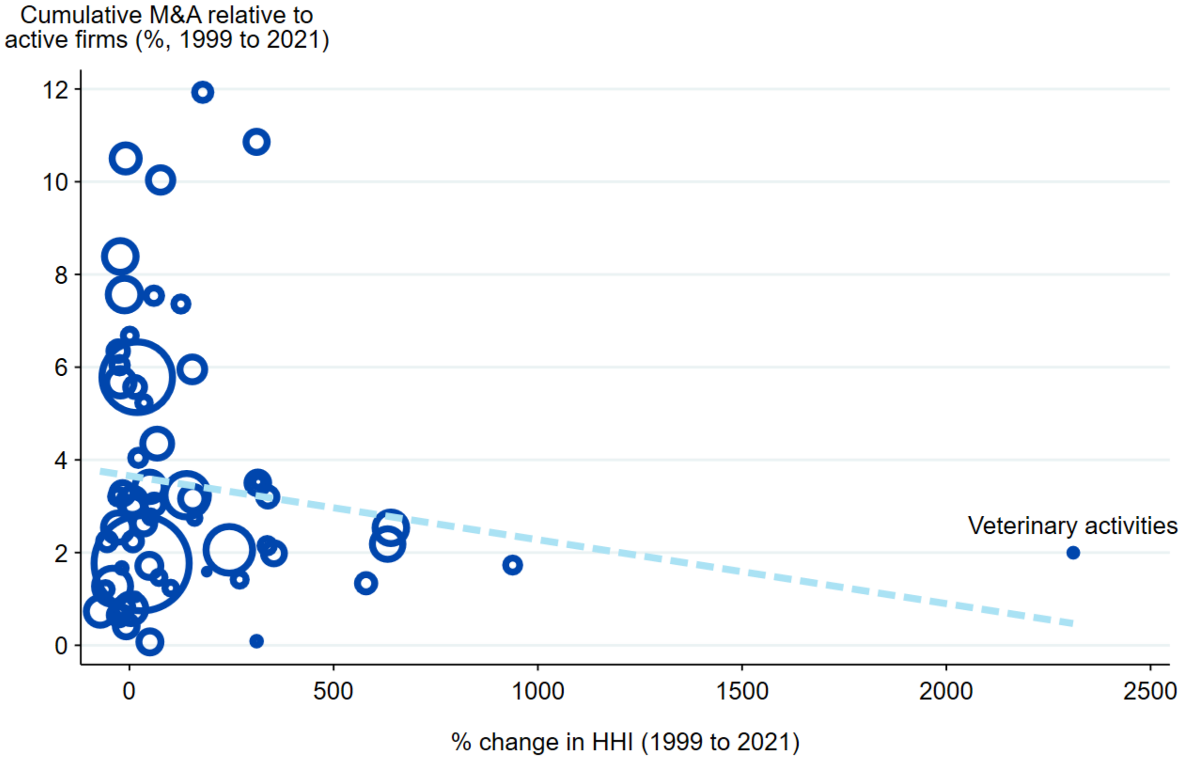
Figure E.35: There is no strong relationship between mergers and acquisitions (M&A) activity and percentage changes in concentration

Panel 1: Scatterplot of the percentage change in the Herfindahl-Hirschman Index (HHI) and cumulative number of mergers and acquisitions as a percentage of average number of active firms by two-digit Standard Industrial Classification (SIC) between 2014 and 2020.
Panel 2: Scatterplot of the percentage change in HHI and mean mergers and acquisitions expenditure as a percentage of turnover by two-digit SIC between 2014 and 2020.
Data from the Business Structural Database (2014-2020) and ONS Merger and Acquisitions Surveys (2014-2020)

Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents sectoral average turnover. Lines of best fit weighted by average turnover, not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and the 2-digit industries that do not have data for the entire period. Sources: the *ONS Merger and Acquisitions Survey* (2014-2020) and the *Business Structure Database* (2014-2020).

Figure E.36: There is no strong relationship between mergers and acquisition (M&A) activity and percentage changes in concentration

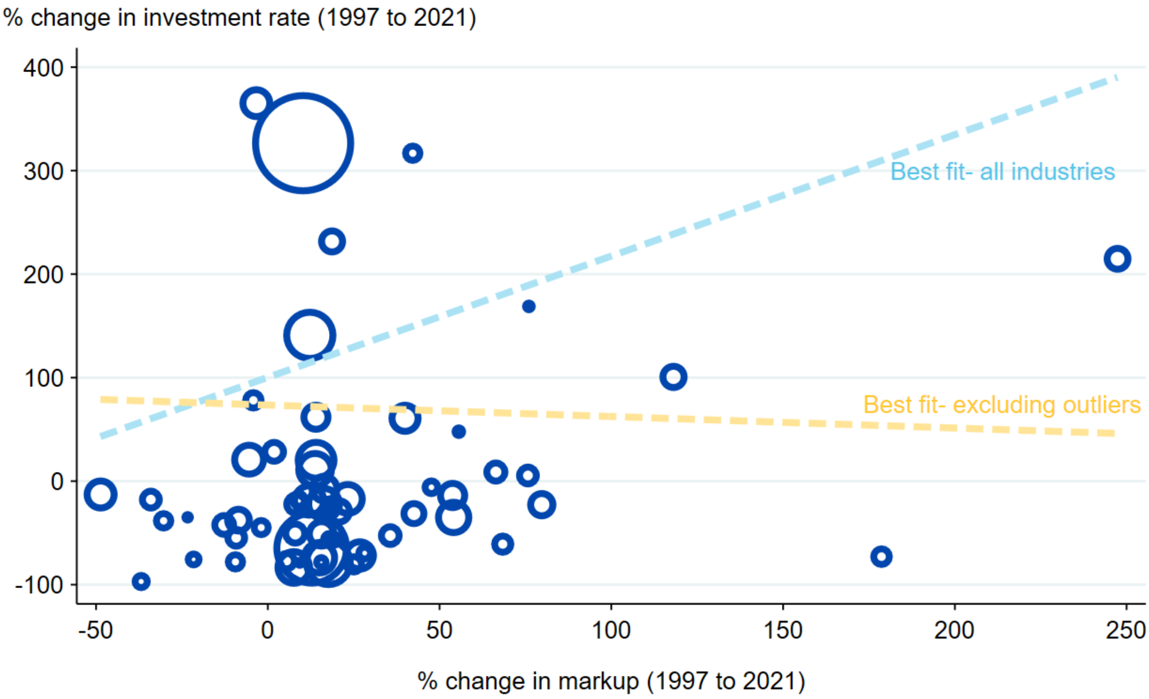
Scatterplot of percentage changes in Herfindahl-Hirschman Index (HHI) and cumulative M&A (local units to enterprises) as a percentage of average active firms between 1999 and 2021 at the two-digit Standard Industrial Classification (SIC) level, from the Longitudinal Business Database (1999-2021) and the Business Structure Database (1999-2021)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents sectoral average turnover. Line of best fit weighted by average turnover, not statistically significant at the 5% level (represented by dashed line). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and the 2-digit industries that do not have data for the entire period. Sources: the *Longitudinal Business Database* (1997-2021) and the *Business Structure Database* (1999-2021).

Figure E.37: There is no strong relationship between the percentage changes in investment rates and markups

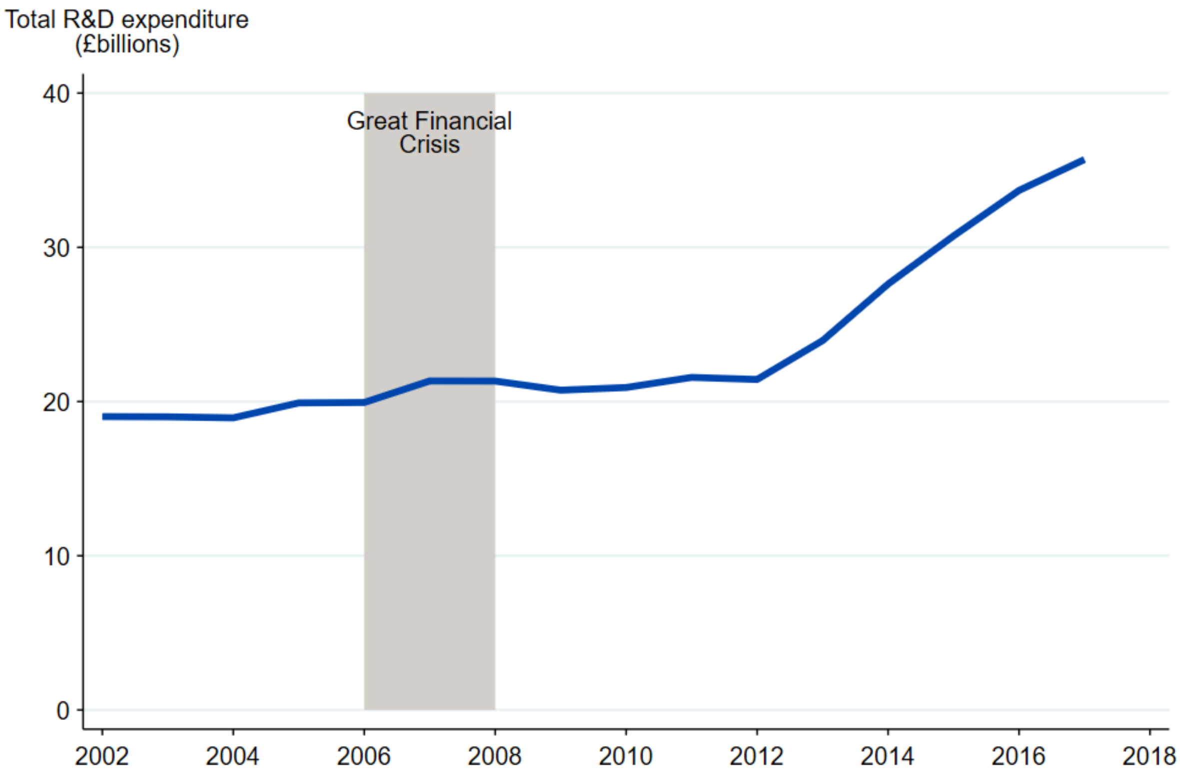
Scatterplot of the percentage change in investment as a percentage of turnover against the percentage change in markups at the two-digit Standard Industrial Classification level, data from Annual Respondents Database X, Annual Business Survey, and ONS Business Investment by Industry and Asset data, 1997 - 2021



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. SIC sector 79 not displayed due to being a significant outlier, but included in the all industry linear fit. Linear fits weighted by turnover and not statistically significant at the 5% level (represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U and 2-digit sectors that we do not have data for in every single year. Investment rate calculated by dividing investment by turnover. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X (1997-2020)* and the *Annual Business Survey (2021)*,

Figure E.38: Research and Development expenditure by known conductors has risen significantly since 2002

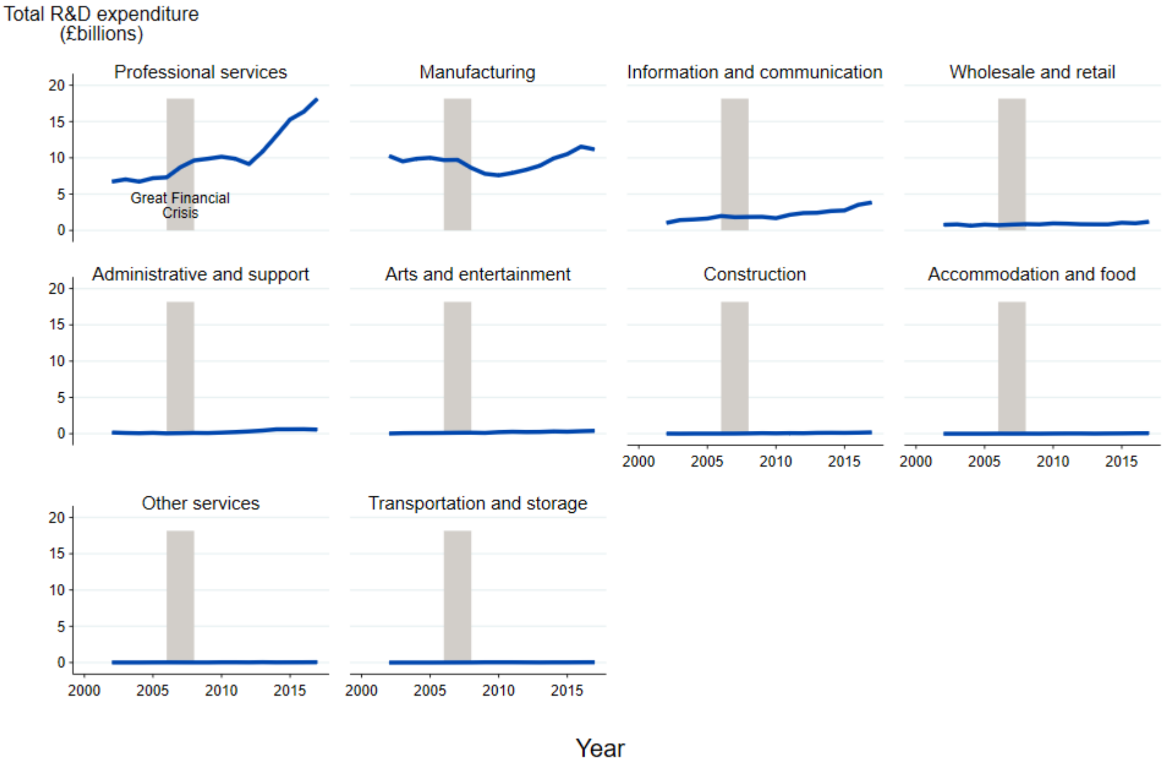
Research and development expenditure by known conductors, 2002 to 2017, from the Business Enterprise Research and Development survey (2002-2017)



Expenditure aggregated from the 2-digit Standard Industrial Classfication (SIC) level. Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Source: *Business Enterprise Research and Development survey* (2002-2017).

Figure 39: Research and Development expenditure by known conductors is highest in professional services and manufacturing sectors

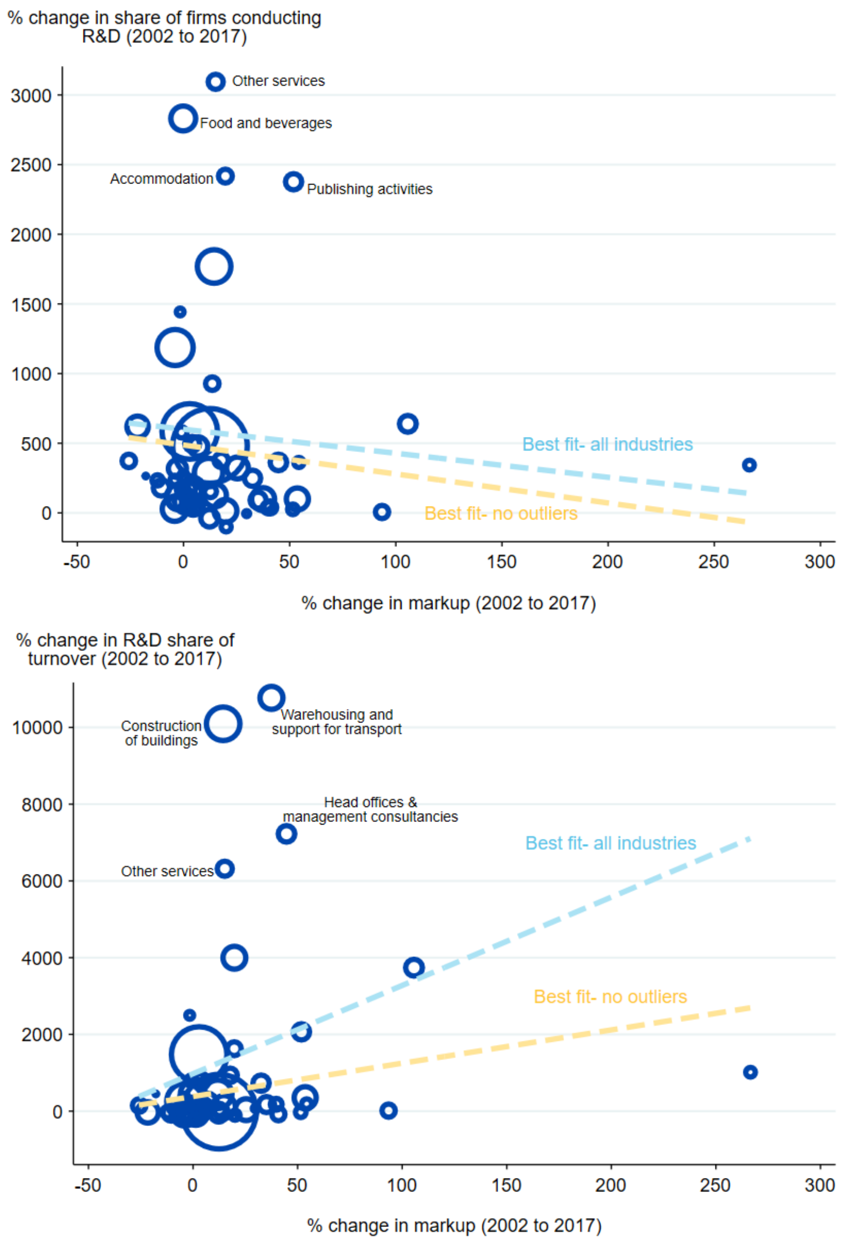
Research and development (R&D) expenditure by known conductors at the Standard Industrial Classification sector level, 2002 to 2017, from the Business Enterprise Research and Development survey (2002-2017)



Expenditure aggregated from the 2-digit Standard Industrial Classfication (SIC) level. Panels ordered based on 2017 expenditure. Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T and U. Source: *Business Enterprise Research and Development survey* (2002-2017).

Figure E.40: There is no strong relationship between research and development activity and markups

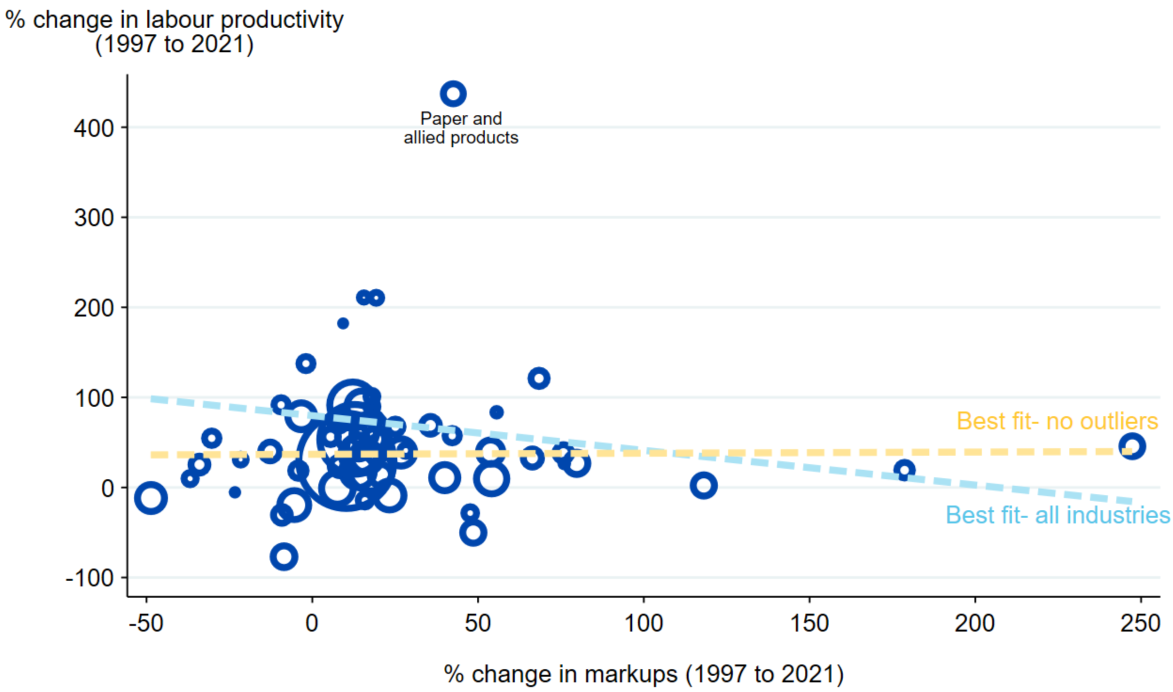
Panel 1: Scatterplot of the percentage changes in the share of active firms that are known R&D conductors and markups at the two-digit Standard Industrial Classification level, from the Business Enterprise Research and Development survey (2002-2017), the Annual Respondents Database x (2002-2017) and the Business Structure Database (2002 to 2017)
Panel 2: Scatterplot of the percentage changes in the R&D expenditure share of turnover and markups between 2002 to 2017, data from Annual Respondents Database X, Annual Business Survey, and Business Enterprise Research and Development Survey



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fits weighted by turnover and not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U. Markups estimated using our baseline approach described in the report. Sources: the *Business Enterprise Research and Development survey* (2002-2017), the *Annual Respondents Database X* (2002-2017) and the *Business Structure Database* (2002-2017).

Figure E.41: There is no strong relationship between labour productivity and markups

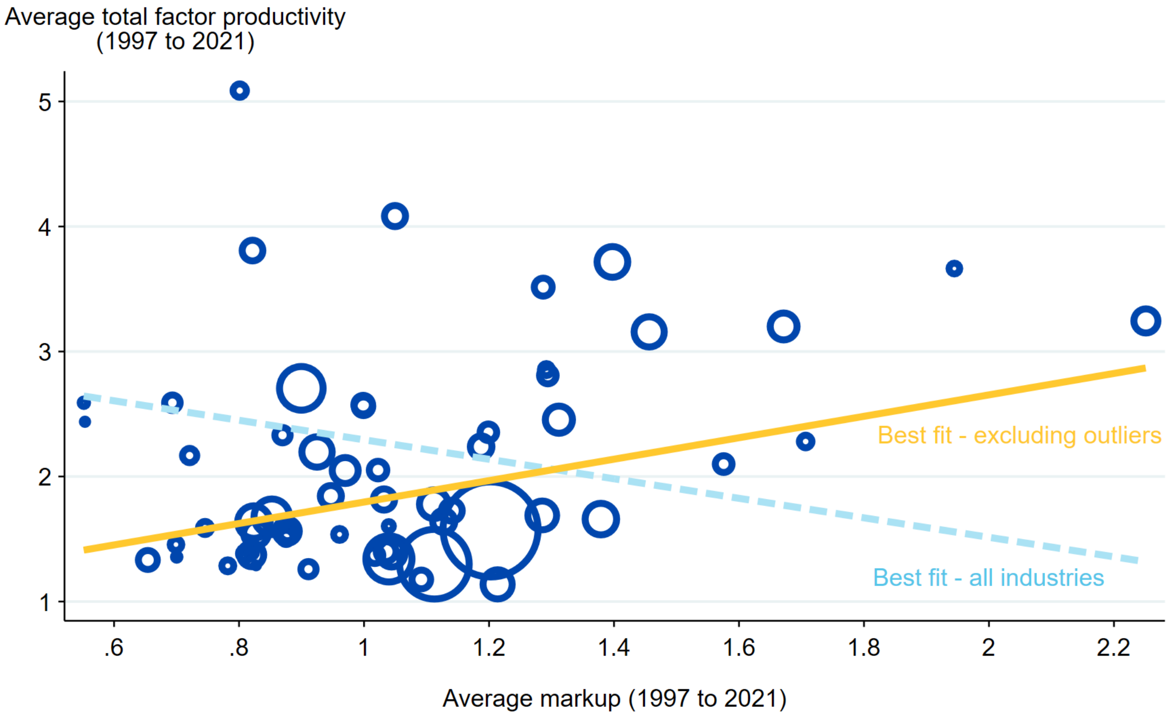
Scatterplot of the percentage changes in labour productivity and markups at the two-digit Standard Industrial Classification level, data from the Annual Respondents Database X, Annual Business Survey and ONS Labour productivity by industry division, 1997-2021



Each data point represents a 2-digit Standard Industrial Classification (SIC) sector, size represents average sectoral turnover. SIC sector telecommunications excluded due to being a significant outlier, but included in all industry linear fit. Linear fits weighted by turnover and not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U and 2-digit sectors that we do not have data for in every single year. Labour productivity defined as real output per hour. Markups are calculated following our baseline approach described in the report. Sources: *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), the *Business Structure Database (1997-2021)* and *Office for National Statistics Labour productivity by industry division (1997-2021).*

Figure E.42: Total factor productivity and markups are positively correlated when excluding outliers

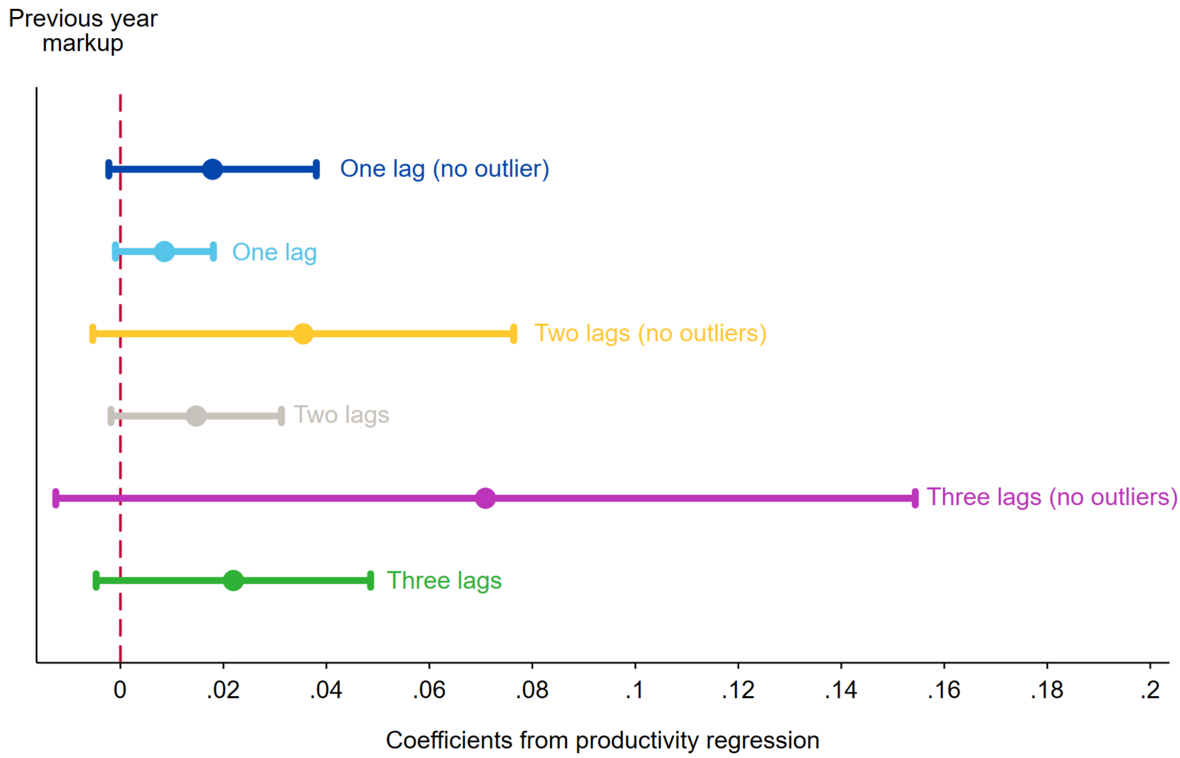
Scatterplot of average total factor productivity and average markups at the two-digit Standard Industrial Classification level. Data from the Annual Respondents Database X (1997-2020), the Annual Business Survey (2021) and the Business Structure Database (1997 to 2022)



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents average sectoral turnover. Linear fits weighted by turnover. The sector programming and broadcasting activities excluded due to being a significant outlier, but included in the all industry best fit (not significant at the 5% level - as represented by the dashed line). Line of best fit becomes significant when excluding outliers (as represented by the solid line). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U and 2-digit sectors that we do not have data for in every single year. Markups estimated using our baseline approach described in the report. Data from: the *Annual Respondents Database X* (1997-2020), the *Annual Business Survey* (2021), and the *Business Structure Database* (1997-2022).

Figure E.43: Labour productivity is not correlated with past markups

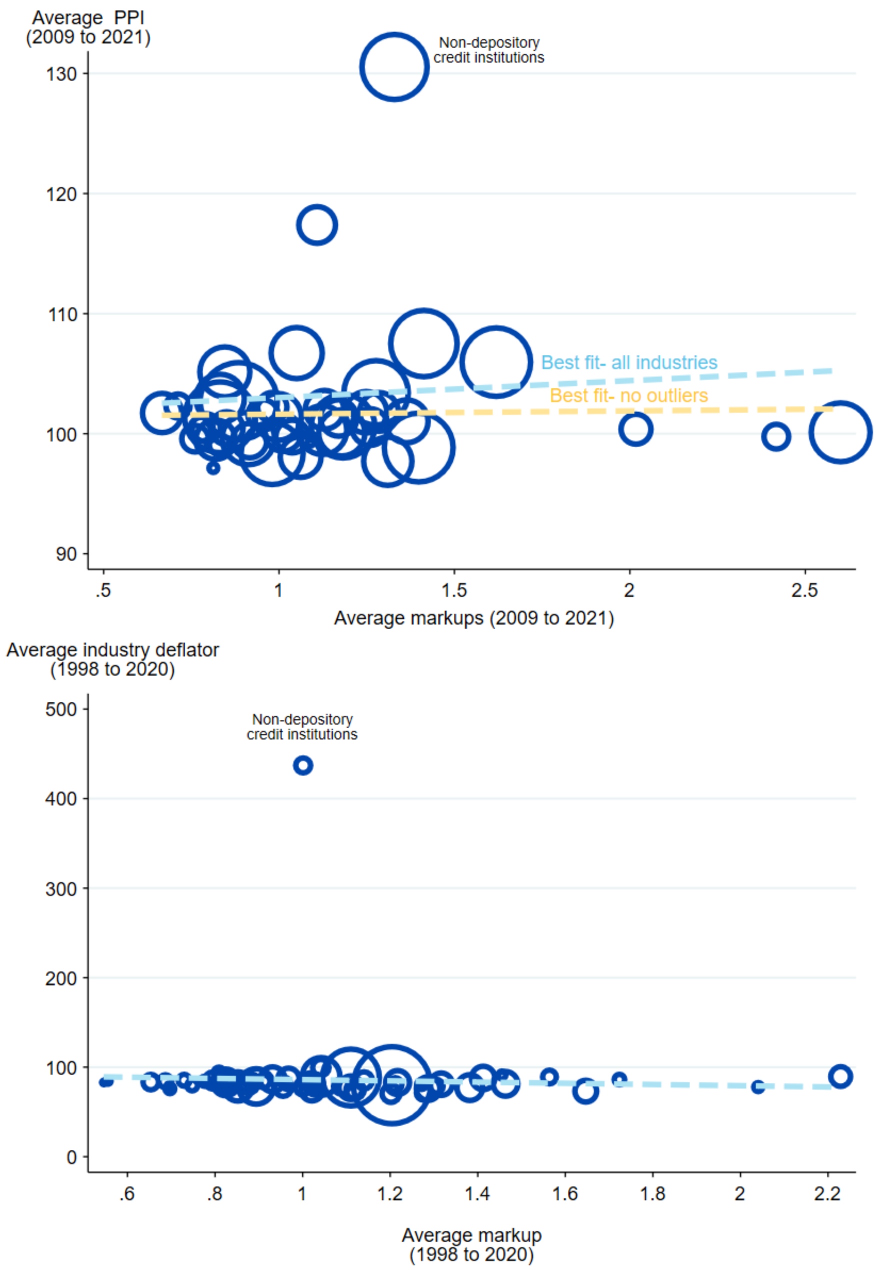
Coefficient plot of labour productivity against the previous year's markup estimates between 1997 to 2021, data from the Annual Respondents Database X and the Annual Business Survey



The coefficients come from various regression specifications of labour productivity (defined as sales per worker) versus lagged markups. Markups are calculated following our baseline approach described in the report. Calculations exclude Standard Industrial Classification (SIC) sectors: A, B, D, E, K, L, O, P, Q, T, U. Data from the *Annual Respondents Database X* (1997-2020) and the *Annual Business Survey* (2021).

Figure E.44: Price changes are uncorrelated with markups

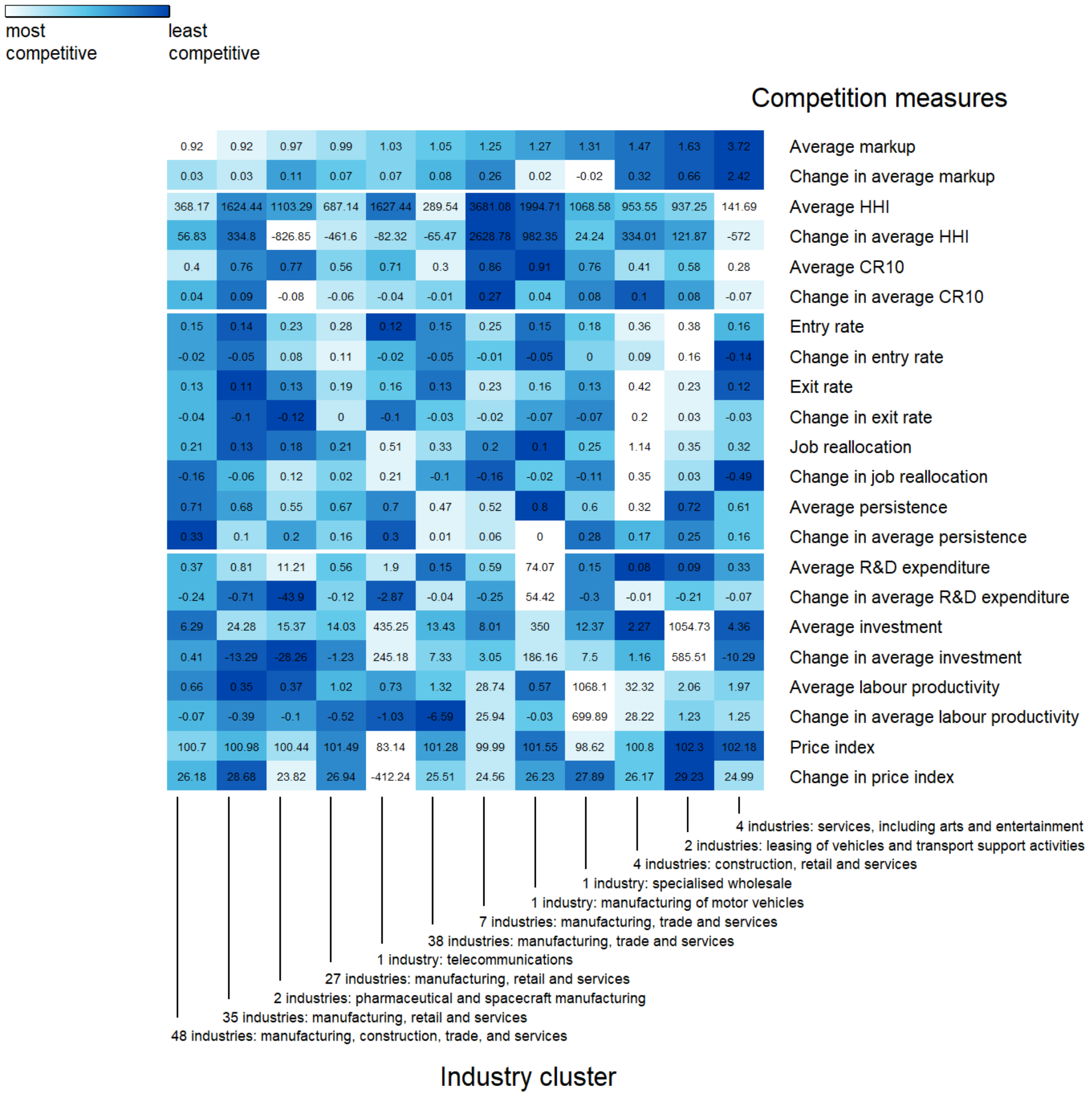
Panel 1: Scatterplot of average markups and average in Producer Price Indices between 2009 and 2021 by two-digit Standard Industrial Classification (SIC) industry, data from the Annual Respondents Database X, Annual Business Survey, ONS Services Producer Price inflation time series and ONS Producer Price Inflation time series.
Panel 2: Scatterplot of average markups and average Industry deflators between 1998 and 2020 by two-digit Standard Industrial Classification (SIC) industry, data from the Annual Respondents Database X, Annual Business Survey and ONS industry deflators and producer and service producer price inflation time series



Each data point represents a 2-digit Standard Industrial Classification (SIC), size represents sectoral average turnover. Lines of best fit weighted by average turnover, not statistically significant at the 5% level (as represented by the dashed lines). Analysis excludes SIC sectors: A, B, D, E, K, L, O, P, Q, T, U, and the 2-digit industries that do not have data for the entire period. Markups estimated using our baseline approach described in the report. Sources: the *Annual Respondents Database X* (1998-2020), the *Annual Business Survey* (2021), the *Business Structure Database* (1998-2021), the ONS *Industry Level Deflators* (1998 to 2020), and the *ONS manufacturing, construction OPI and SPPI for all other sectors* (2009-2021).

Figure E.45: Industries vary widely in their structure and conduct

Heatmap from a k-means clustering exercise at the three-digit Standard Industrial Classification (SIC) level. Clusters are ordered from lower to higher markup. Data from Annual Respondents Database X (ARDx) 1997-2020, Annual Business Database 2021, Business Enterprise Research and Development survey (BERD) 1995-2017, Business Structure Database (BSD) 1997-2022, Industry level deflators by Office for National Statistics 1997-2023, Longitudinal Business Database (LBD) 1997-2021. GB only



Each cell gives the intensity of competition in each selected measure for a given cluster of 3-digit Standard Industrial Classification (SIC) industries. Darker shades indicate less competition. The analysis is done for the period 2005-2020 with the exception of R&D measures that refer to 2005-2017 and excluding SIC sectors: A, B, D, E, K, L, O, P, Q, T, U. Markups are calculated following our baseline approach described in the report. Clusters are ranked by their average markup over that period. Data are 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).

F. Additional tables

Table F.1: Firm-level markup regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: *Markups*							
Age	0.009	0.243***	0.256***	0.259***	0.253***	0.182	0.122**
	(0.031)	(0.071)	(0.071)	(0.071)	(0.071)	(0.093)	(0.041)
Age squared	-0.094**	-0.268***	-0.272***	-0.275***	-0.273***	-0.125	-0.0519*
	(0.034)	(0.063)	(0.063)	(0.062)	(0.063)	(0.066)	(0.022)
Log Employment	0.190***	-0.373***	-0.367***	-0.366***	-0.367***	-0.248***	-0.140***
	(0.012)	(0.081)	(0.081)	(0.081)	(0.082)	(0.060)	(0.029)
Profit margin	0.948***	1.499***	1.502***	1.503***	1.503***	1.479***	0.748***
	(0.039)	(0.058)	(0.058)	(0.058)	(0.058)	(0.123)	(0.039)
Labour share	0.353***	0.739***	0.744***	0.748***	0.749***	0.713***	0.588***
	(0.031)	(0.062)	(0.062)	(0.063)	(0.063)	(0.123)	(0.084)
Sales per worker	0.037*	0.002	0.002	0.002	0.002	-0.001*	-0.000
	(0.018)	(0.029)	(0.029)	(0.029)	(0.028)	(0.000)	(0.000)
Fixed effects:							
Year	✓	✓	✓	✓	✓	✓	✓
Firm		✓	✓	✓	✓	✓	✓
SIC			1d	2d	3d	3d	3d
Weighted?						✓	✓
Remove outliers?							✓
Adj. R2	0.016	0.422	0.422	0.422	0.422	0.639	0.425
Observations	662,616	430,094	430,094	430,094	430,094	430,094	423,758

Note: Data from the Annual Respondents Database x (1997-2020) the Annual Business Survey (2021). Fixed effects at the reporting unit level. Weighting by turnover. Outliers are top/bottom 1% of markups by two-digit SIC by year. Standard errors are reported below the regression coefficients in parentheses. They are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table F.2: Firm-level markup regressions with full set of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: *Markups*							
Age	0.0325	0.414	0.419	0.428	0.398*	-0.142	0.012
	(0.055)	(0.240)	(0.229)	(0.229)	(0.187)	(0.167)	(0.032)
Log Employment	0.136***	-0.218	-0.214	-0.220	-0.208	-0.195	-0.168***
	(0.011)	(0.125)	(0.127)	(0.128)	(0.129)	(0.190)	(0.030)
Profit margin	1.024***	1.268***	1.269***	1.270***	1.275***	1.136***	0.470***
	(0.067)	(0.086)	(0.086)	(0.086)	(0.086)	(0.227)	(0.030)
Labour share	0.006	0.600***	0.602***	0.602***	0.604***	0.638***	0.235***
	(0.028)	(0.069)	(0.069)	(0.069)	(0.068)	(0.246)	(0.104)
Sales per worker	0.023**	-0.014	-0.014	-0.016	-0.014	-0.000	0.000
	(0.008)	(0.021)	(0.021)	(0.021)	(0.021)	(0.001)	(0.000)
Fixed effects:							
Year	✓	✓	✓	✓	✓	✓	✓
Firm		✓	✓	✓	✓	✓	✓
SIC			1d	2d	3d	3d	3d
Weighted?						✓	✓
Remove outliers?							✓
Adj. R2	0.033	0.236	0.237	0.238	0.238	0.530	0.957
Observations	106,751	64,966	64,966	64,966	64,966	64,966	64,178

Note: Data from the Annual Respondents Database x (1997-2020) and the Annual Business Survey (2021). Fixed effects at the reporting unit level. Other controls: **age squared, capex, investment in software, investment in equipment, and indicators for multiple local and reporting units and exporting**. Weighting by turnover. Outliers are top/bottom 1% of markups by two-digit SIC by year. Standard errors are reported below the regression coefficients in parentheses. They are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table F.3: list of SIC industries in each cluster

Cluster	Count	Industries
1	48	102: Processing and preserving of fish, crustaceans and molluscs 107: Manufacture of bakery and farinaceous products 131: Preparation and spinning of textile fibres 132: Weaving of textiles 139: Manufacture of other textiles 161: Sawmilling and planing of wood 162: Manufacture of products of wood, cork, straw and plaiting materials 181: Printing and service activities related to printing 222: Manufacture of plastics products 242: Manufacture of tubes, pipes, hollow profiles and related fittings, of steel 255: Forging, pressing, stamping and roll-forming of metal; powder metallurgy 259: Manufacture of other fabricated metal products 263: Manufacture of communication equipment 267: Manufacture of optical instruments and photographic equipment 274: Manufacture of electric lighting equipment 282: Manufacture of other general-purpose machinery 284: Manufacture of metal forming machinery and machine tools 292: Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers 293: Manufacture of parts and accessories for motor vehicles 310: Manufacture of furniture 412: Construction of residential and non-residential buildings 421: Construction of roads and railways 429: Construction of other civil engineering projects 439: Other specialised construction activities 451: Sale of motor vehicles 452: Maintenance and repair of motor vehicles 454: Sale, maintenance and repair of motorcycles and related parts and accessories 462: Wholesale of agricultural raw materials and live animals 463: Wholesale of food, beverages and tobacco 465: Wholesale of information and communication equipment 466: Wholesale of other machinery, equipment and supplies 469: Non-specialised wholesale trade 479: Retail trade not in stores, stalls or markets 552: Holiday and other short-stay accommodation 553: Camping grounds, recreational vehicle parks and trailer parks 563: Beverage serving activities 620: Computer programming, consultancy and related activities 691: Legal activities 692: Accounting, bookkeeping and auditing activities; tax consultancy 712: Technical testing and analysis 722: Research and experimental development on social sciences and humanities 742: Photographic activities 910: Libraries, archives, museums and other cultural activities 931: Sports activities 932: Amusement and recreation activities 941: Activities of business, employers and professional membership organisations 949: Activities of other membership organisations 952: Repair of personal and household goods

2	**35**	104: Manufacture of vegetable and animal oils and fats 105: Manufacture of dairy products 110: Manufacture of beverages 151: Manufacture of leather and related products 152: Manufacture of footwear 172: Manufacture of articles of paper and paperboard 201: Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms 212: Manufacture of pharmaceutical preparations 221: Manufacture of rubber products 231: Manufacture of glass and glass products 232: Manufacture of refractory products 233: Manufacture of clay building materials 234: Manufacture of other porcelain and ceramic products 236: Manufacture of articles of concrete, cement and plaster 241: Manufacture of basic iron and steel and of ferro-alloys 243: Manufacture of other products of first processing of steel 244: Manufacture of basic precious and other non-ferrous metals 245: Casting of metals 252: Manufacture of tanks, reservoirs and containers of metal 254: Manufacture of weapons and ammunition 262: Manufacture of computers and peripheral equipment 272: Manufacture of batteries and accumulators 273: Manufacture of wiring and wiring devices 275: Manufacture of domestic appliances 281: Manufacture of general purpose machinery 289: Manufacture of other special-purpose machinery 321: Manufacture of jewellery, bijouterie and related articles 324: Manufacture of games and toys 471: Retail sale in non-specialised stores 475: Retail sale of other household equipment in specialised stores 476: Retail sale of cultural and recreation goods in specialised stores 491: Passenger rail transport, interurban 495: Transport via pipeline 942: Activities of trade unions 951: Repair of computers and communication equipment
3	**2**	211: Manufacture of basic pharmaceutical products 303: Manufacture of air and spacecraft and related machinery
4	**27**	101: Processing and preserving of meat and production of meat products 103: Processing and preserving of fruit and vegetables 106: Manufacture of grain mill products, starches and starch products 108: Manufacture of other food products 109: Manufacture of prepared animal feeds 143: Manufacture of knitted and crocheted apparel 171: Manufacture of pulp, paper and paperboard 202: Manufacture of pesticides and other agrochemical products 203: Manufacture of paints, varnishes and similar coatings, printing ink and mastics 204: Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations 261: Manufacture of electronic components and boards 264: Manufacture of consumer electronics

		265: Manufacture of instruments and appliances for measuring, testing and navigation; watches and clocks 309: Manufacture of transport equipment n.e.c 322: Manufacture of musical instruments 323: Manufacture of sports goods 325: Manufacture of medical and dental instruments and supplies 331: Repair of fabricated metal products, machinery and equipment 332: Installation of industrial machinery and equipment 477: Retail sale of other goods in specialised stores 493: Other passenger land transport 581: Publishing of books, periodicals and other publishing activities 582: Software publishing 631: Data processing, hosting and related activities; web portals 721: Research and experimental development on natural sciences and engineering 799: Other reservation service and related activities 801: Private security activities
5	**1**	619: Other telecommunications activities
6	**38**	133: Finishing of textiles 141: Manufacture of wearing apparel, except fur apparel 182: Reproduction of recorded media 237: Cutting, shaping and finishing of stone 251: Manufacture of structural metal products 256: Treatment and coating of metals; machining 257: Manufacture of cutlery, tools and general hardware 271: Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus 329: Manufacturing n.e.c 431: Demolition and site preparation 432: Electrical, plumbing and other construction installation activities 433: Building completion and finishing 453: Sale of motor vehicle parts and accessories 464: Wholesale of household goods 472: Retail sale of food, beverages and tobacco in specialised stores 473: Retail sale of automotive fuel in specialised stores 494: Freight transport by road and removal services 521: Warehousing and storage 551: Hotels and similar accommodation 561: Restaurants and mobile food service activities 562: Event catering and other food service activities 591: Motion picture, video and television programme activities 702: Management consultancy activities 711: Architectural and engineering activities and related technical consultancy 731: Advertising 732: Market research and public opinion polling 741: Specialised design activities 749: Other professional, scientific and technical activities nec 750: Veterinary activities 772: Renting and leasing of personal and household goods 773: Renting and leasing of other machinery, equipment and tangible goods 781: Activities of employment placement agencies 791: Travel agency and tour operator activities 803: Investigation activities 812: Cleaning activities 813: Landscape service activities

		829: Business support service activities n.e.c 960: Other personal service activities
7	**7**	205: Manufacture of other chemical products 206: Manufacture of man-made fibres 239: Manufacture of abrasive products and non-metallic mineral products n.e.c 301: Building of ships and boats 461: Wholesale on a fee or contract basis 474: Retail sale of information and communication equipment in specialised stores 822: Activities of call centres
8	**1**	291: Manufacture of motor vehicles
9	**1**	467: Other specialised wholesale
10	**4**	411: Development of building projects 478: Retail sale via stalls and markets 592: Sound recording and music publishing activities 821: Office administrative and support activities
11	**2**	522: Support activities for transportation 771: Renting and leasing of motor vehicles
12	**4**	639: Other information service activities 782: Temporary employment agency activities 823: Organisation of conventions and trade shows 900: Creative, arts and entertainment activities

Table F.4: CompNet international comparison table

Year	Country	Mean markup (indexed to 100 in 2011)	HHI (indexed to 100 in 2011)	Job creation (indexed to 100 in 2011)	Job destruction (indexed to 100 in 2011)
2000	Belgium	93	94		
2001	Belgium	94	76	110	83
2002	Belgium	95	79	72	165
2003	Belgium	98	80	71	148
2004	Belgium	97	83	76	120
2005	Belgium	97	79	85	112
2006	Belgium	96	81	98	106
2007	Belgium	97	89	99	104
2008	Belgium	98	81	87	111
2009	Belgium	98	77	57	207
2010	Belgium	100	95	80	121
2011	Belgium	100	100	100	100
2012	Belgium	100	106	71	128
2013	Belgium	102	91	68	141
2014	Belgium	103	94	83	123
2015	Belgium	104	94	85	106
2016	Belgium	103	92	86	101
2017	Belgium	103	110	97	72
2018	Belgium	103	118	81	94
2019	Belgium	105	81	86	123
2020	Belgium	100	100	59	150
2002	Croatia	93	82		
2003	Croatia	102	59	133	98
2004	Croatia	104	60	125	86
2005	Croatia	104	54	116	83
2006	Croatia	104	62	140	64
2007	Croatia	101	69	154	59
2008	Croatia	99	76	134	72
2009	Croatia	111	85	72	133
2010	Croatia	111	102	80	133
2011	Croatia	100	100	100	100
2012	Croatia	95	106	107	113
2013	Croatia	94	103	127	109
2014	Croatia	98	104	129	123
2015	Croatia	97	112	124	73
2016	Croatia	105	81	123	64
2017	Croatia	106	74	125	66
2018	Croatia	109	68	134	84
2019	Croatia	109	65	124	64
2020	Croatia	116	71	84	108
2021	Croatia	117	66	106	62

2005	Czech Republic	97	84		
2006	Czech Republic	97	86	103	95
2007	Czech Republic	99	79	108	91
2008	Czech Republic	99	72	92	126
2009	Czech Republic	100	80	57	238
2010	Czech Republic	100	94	83	129
2011	Czech Republic	100	100	100	100
2012	Czech Republic	100	83	76	109
2013	Czech Republic	100	89	78	114
2014	Czech Republic	102	104	85	83
2015	Czech Republic	103	103	92	79
2016	Czech Republic	105	113	89	80
2017	Czech Republic	105	129	86	79
2018	Czech Republic	106	123	76	98
2019	Czech Republic	107	139	65	113
2020	Czech Republic	106	123	51	144
2001	Germany	87	269		
2002	Germany	89	275	56	140
2003	Germany	98	147	56	408
2004	Germany	97	142	80	152
2005	Germany	98	159	80	155
2006	Germany	99	101	93	120
2007	Germany	100	107	99	105
2008	Germany	103	121	86	132
2009	Germany	100	84	69	191
2010	Germany	101	98	98	127
2011	Germany	100	100	100	100
2012	Germany	102	113	83	107
2013	Germany	104	119	78	110
2014	Germany	103	124	83	109
2015	Germany	103	131	83	115
2016	Germany	102	128	77	112
2017	Germany	101	126	92	109
2018	Germany	102	133	94	115
2003	Hungary	98	42		
2004	Hungary	99	68	93	132
2005	Hungary	99	73	95	143
2006	Hungary	100	58	112	126
2007	Hungary	101	59	111	129
2008	Hungary	100	68	104	149
2009	Hungary	100	91	54	207
2010	Hungary	100	70	89	127
2011	Hungary	100	100	100	100
2012	Hungary	100	148	76	124
2013	Hungary	102	146	73	110

2014	Hungary	104	164	104	90
2015	Hungary	106	147	81	83
2016	Hungary	107	59	85	90
2017	Hungary	109	109	89	81
2018	Hungary	111	98	82	85
2019	Hungary	113	107	79	99
2020	Hungary	112	98	64	159
2006	Italy	101	56		
2007	Italy	101	95	119	163
2008	Italy	100	87	110	91
2009	Italy	100	93	80	152
2010	Italy	100	96	89	150
2011	Italy	100	100	100	100
2012	Italy	100	88	93	95
2013	Italy	101	81	85	109
2014	Italy	102	76	99	103
2015	Italy	103	77	102	84
2016	Italy	103	77	113	75
2017	Italy	103	76	121	69
2018	Italy	103	76	112	62
2019	Italy	104	73	101	83
2020	Italy	101	86	79	135
2007	Latvia	105	58		
2008	Latvia	102	74	77	187
2009	Latvia	93	111	25	357
2010	Latvia	96	112	64	190
2011	Latvia	100	100	100	100
2012	Latvia	102	93	95	88
2013	Latvia	101	90	79	94
2014	Latvia	101	90	81	96
2015	Latvia	104	96	75	111
2016	Latvia	99	111	79	114
2017	Latvia	102	104	82	90
2018	Latvia	104	98	85	79
2019	Latvia	111	94	75	82
2000	Lithuania	93	68		
2001	Lithuania	95	81	107	190
2002	Lithuania	96	85	150	150
2003	Lithuania	96	82	157	118
2004	Lithuania	96	82	131	144
2005	Lithuania	96	86	112	144
2006	Lithuania	98	73	119	137
2007	Lithuania	102	75	110	138
2008	Lithuania	103	88	79	187
2009	Lithuania	103	121	38	386

2010	Lithuania	99	107	60	210
2011	Lithuania	100	100	100	100
2012	Lithuania	100	95	91	105
2013	Lithuania	101	87	85	96
2014	Lithuania	104	81	90	93
2015	Lithuania	106	82	79	103
2016	Lithuania	105	75	80	105
2017	Lithuania	107	69	91	113
2018	Lithuania	109	67	83	116
2019	Lithuania	110	67	91	118
2020	Lithuania	112	73	73	171
2010	Malta	107	162		
2011	Malta	100	100	100	100
2012	Malta	102	31	85	86
2013	Malta	102	92	95	70
2014	Malta	104	53	120	64
2015	Malta	107	40	135	71
2016	Malta	108	38	110	94
2017	Malta	106	44	141	63
2018	Malta	107	37	130	83
2019	Malta	106	31	133	81
2020	Malta	103	26	88	139
2007	Netherlands	100	88		
2008	Netherlands	100	75	142	112
2009	Netherlands	100	59	93	181
2010	Netherlands	100	73	88	153
2011	Netherlands	100	100	100	100
2012	Netherlands	100	64	93	103
2013	Netherlands	100	99	85	138
2014	Netherlands	101	89	105	111
2015	Netherlands	102	55	132	84
2016	Netherlands	104	52	139	80
2017	Netherlands	103	54	148	85
2018	Netherlands	103	55	206	75
2019	Netherlands	104	54	107	190
2002	Poland	96	104		
2003	Poland	93	96	103	119
2004	Poland	92	107	122	104
2005	Poland	95	110	123	89
2006	Poland	97	102	153	71
2007	Poland	100	95	153	67
2008	Poland	104	92	121	105
2009	Poland	97	89	76	135
2010	Poland	101	97	106	84
2011	Poland	100	100	100	100

2012	Poland	100	105	82	107
2013	Poland	100	112	104	87
2014	Poland	100	116	116	73
2015	Poland	103	118	112	71
2016	Poland	103	122	116	63
2017	Poland	106	124	117	64
2018	Poland	108	111	104	77
2019	Poland	106	114	90	75
2020	Poland	104	129	70	96
2004	Portugal		77		
2005	Portugal		86	84	60
2006	Portugal		83	168	103
2007	Portugal		80	158	82
2008	Portugal		84	168	84
2009	Portugal		91	112	111
2010	Portugal	102	97	129	92
2011	Portugal	100	100	100	100
2012	Portugal	99	109	82	131
2013	Portugal	101	102	108	105
2014	Portugal	102	108	150	72
2015	Portugal	103	104	150	62
2016	Portugal	104	90	157	65
2017	Portugal	105	93	167	55
2018	Portugal	106	106	165	63
2019	Portugal	106	109	148	66
2020	Portugal	104	76	97	138
2005	Romania	101	115		
2006	Romania	102	100	91	156
2007	Romania	108	83	101	140
2008	Romania	105	71	88	142
2009	Romania	100	97	43	245
2010	Romania	101	110	67	174
2011	Romania	100	100	100	100
2012	Romania	97	103	76	108
2013	Romania	99	135	74	114
2014	Romania	101	132	81	108
2015	Romania	105	125	90	96
2016	Romania	108	130	85	97
2017	Romania	110	81	76	97
2018	Romania	111	80	67	104
2019	Romania	113	80	63	108
2020	Romania	113	111	51	149
2000	Slovakia	76	120		
2001	Slovakia	80	104	76	156
2002	Slovakia	80	114	78	225

2003	Slovakia	77	206	70	138
2004	Slovakia	80	169	80	151
2005	Slovakia	87	130	77	128
2006	Slovakia	90	155	90	92
2007	Slovakia	94	157	106	90
2008	Slovakia	97	117	90	93
2009	Slovakia	104	76	50	221
2010	Slovakia	102	80	86	123
2011	Slovakia	100	100	100	100
2012	Slovakia	101	134	84	99
2013	Slovakia	101	135	73	110
2014	Slovakia	100	122	89	77
2015	Slovakia	98	131	97	64
2016	Slovakia	98	135	98	73
2017	Slovakia	99	121	101	70
2018	Slovakia	99	164	88	73
2019	Slovakia	99	158	64	102
2020	Slovakia	102	142	53	125
2002	Slovenia	97	73		
2003	Slovenia	99	60	64	105
2004	Slovenia	99	74	103	85
2005	Slovenia	98	97	97	81
2006	Slovenia	99	109	128	99
2007	Slovenia	100	103	101	74
2008	Slovenia	100	90	88	83
2009	Slovenia	100	104	46	173
2010	Slovenia	100	99	65	120
2011	Slovenia	100	100	100	100
2012	Slovenia	100	93	81	94
2013	Slovenia	102	97	60	98
2014	Slovenia	103	97	80	62
2015	Slovenia	105	95	89	60
2016	Slovenia	106	82	98	48
2017	Slovenia	106	76	116	48
2018	Slovenia	106	70	110	46
2019	Slovenia	107	70	94	54
2020	Slovenia	108	74	58	125
2021	Slovenia	111	54	93	74
2008	Spain	97	97		
2009	Spain	98	111	54	171
2010	Spain	99	105	89	106
2011	Spain	100	100	100	100
2012	Spain	102	107	78	116
2013	Spain	103	123	84	106
2014	Spain	103	121	103	93

2015	Spain	103	108	128	52
2016	Spain	104	110	138	55
2017	Spain	105	113	141	50
2018	Spain	105	97	118	66
2019	Spain	107	110	113	57
2020	Spain	107	115	76	246
2009	Switzerland	99	106		
2010	Switzerland	103	96	92	140
2011	Switzerland	100	100	100	100
2012	Switzerland	99	107	89	114
2013	Switzerland	103	92	97	109
2014	Switzerland	104	104	87	137
2015	Switzerland	106	102	85	124
2016	Switzerland	105	97	82	126
2017	Switzerland	105	113	111	120
2018	Switzerland	108	114	101	132
2019	Switzerland	108	121	86	117
2020	Switzerland	108	116	78	174
1997	United Kingdom	89	47		
1998	United Kingdom	94	50	240	153
1999	United Kingdom	98	48	187	167
2000	United Kingdom	107	51	250	270
2001	United Kingdom	107	56	160	166
2002	United Kingdom	106	55	144	252
2003	United Kingdom	102	60	121	192
2004	United Kingdom	105	60	125	161
2005	United Kingdom	107	60	133	152
2006	United Kingdom	109	59	125	161
2007	United Kingdom	115	71	134	128
2008	United Kingdom	103	89	121	125
2009	United Kingdom	94	101	101	174
2010	United Kingdom	99	100	98	165
2011	United Kingdom	100	100	100	100
2012	United Kingdom	106	97	120	111
2013	United Kingdom	105	94	115	119
2014	United Kingdom	110	88	104	91
2015	United Kingdom	121	82	120	87
2016	United Kingdom	111	86	112	125
2017	United Kingdom	104	83	88	82
2018	United Kingdom	103	81	113	107
2019	United Kingdom	103	75	100	108