Appendix A: Concentration[1]

Background

0. Measures of market structure are an intuitively simple way to assess the level of competition across an economy. They do not provide a view on the outcomes of markets for consumers, or on the underlying forces which determine the level of competition within a market, but may indicate the way in which a market is functioning, especially when combined with other metrics. For example, where a market has a small number of firms with high market shares (a highly concentrated market), this may indicate a lack of competition caused by high barriers to entry, or may be the result of very strong competition with only the most efficient firms surviving.

1. Concentration is a widely used competition indicator, and we have calculated a number of concentration metrics at the industry level. These metrics measure how concentrated industry turnover is among a small number of firms. Care must be taken with industry results as the industries identified by the Standard Industrial Classification (SIC) system of industrial classification, used throughout the data sources this report relies on, are unlikely to represent markets in the economic sense.[2] Still, industry concentration is widely used and the stylised facts it reveals about trends in the structure of the economy may be informative of the state of competition.

2. Concentration measures do not tell us how dynamic an industry is – ie whether the same firms take the same industry shares year after year, or whether there is a lot of change in the composition of an industry in terms of the firms within it. Measures of industry dynamics, therefore, can augment concentration metrics and improve our understanding of competition. Rates of firm entry and exit are widely-used dynamic measures of competition – in competitive markets we expect to see that new firms are able to enter, and that less efficient firms exit. We have also estimated the degree of churn among the top firms (ie whether the same firms stay at the top or are frequently replaced) in industries to complement this.

[1] This work was produced using statistical data from ONS. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.
[2] This is discussed in the Chapter 2, paragraph 2.9. Evidence indicates that SIC codes are likely to be far broader than economic markets in product scope. This means that the results of this analysis would not be informative for any analysis of competition required in exercise of the CMA's enforcement functions.

3. It is important to consider market structure metrics (both concentration metrics and dynamic metrics) carefully and with the caveats (set out in detail at paragraphs 2.7 and 2.8 in Chapter 2) in mind.

Methodology

4. Before undertaking our own research, we reviewed past studies and their methodologies. Below, we summarise their approaches in measuring and analysing concentration, before describing our own approach.

Methodologies of existing concentration studies

5. The Resolution Foundation[3] used data from the Office for National Statistics' (ONS) Business Structure Database (BSD)[4] to analyse concentration in the UK for the period 2003/04 to 2015/16 in three ways:

   (a) First, it analysed the share of the top 100 firms in the entire economy using two-year rolling averages.

   (b) Second, it analysed economy wide average HHI, CR5, CR10 and CR20 measures. To do this it first calculated these metrics at the subsector level (based on the five-digit SIC code level) and then combined these subsector estimates to calculate weighted[5] averages at the economy-wide level. These metrics were calculated using two-year rolling averages.

   (c) Third, it assessed industry level CR5 by using the calculations (noted at 2.11 (b)) of this metric at the subsector level (based on the five-digit SIC code level) and then aggregating these subsector estimates to calculate

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[3] Resolution Foundation (2018), Is everybody concentrating? Recent trends in product and labour market concentration in the UK

[4] The BSD data is essentially an annual snapshot of Inter-Departmental Business Register (IDBR) data. The BSD, and thus also the IDBR, contains data on all firms active in the UK that are VAT registered or operate a Pay As You Earn (PAYE) scheme. It thus includes a very large proportion of UK businesses: in terms of revenue, the coverage of the BSD is estimated as being 98-99% (ONS BSD User Guide, 2006). The businesses excluded from the dataset will include businesses such as sole traders and self-employed workers who have revenue below the VAT threshold. By number these are estimated to be around half of all UK businesses, though they are only 1-2% by revenue. A key limitation is that all of a business' revenues will be ascribed to its primary industry – this may have the effect of making industries appear to be more concentrated than they really are, by reducing the number of firms in the secondary industries and by inflating the business's apparent size in the primary industry. Furthermore, this can lead to firms moving sectors from year to year based on changes in their revenue streams. Another crucial limitation of this dataset is that there is a lag in the BSD data due to the way the data is collected. According to Aguda, O., Hwang, K.I., & Savagar, A. (2019), *Product Market Concentration and Productivity in the UK,* this means that BSD 2014 data could include data on economic activity dating as far back as 2012. We understand that no study corrected for this lag in their concentration measures.

[5] We understand these metrics to be based on a weighted average where each subsector is weighted by turnover.

averages at the industry level (rather than at the level of the whole economy).

6. In relation to its economy wide average concentration metrics, the Resolution Foundation also considered the cause of any observed increase. In particular, changes in the economy wide average can be driven by:

   (a) changes in concentration at the subsector level (ie individual subsectors are getting more or less concentrated); or

   (b) changes in the relative size of the different subsectors (ie more concentrated subsectors increase in size relative to less concentrated subsectors or vice versa).

   The Resolution Foundation estimated the extent to which these two factors drove the results it found (see paragraphs from 2.17 in Chapter 2).

7. This analysis excluded fuel-wholesale and finance-related subsectors on the grounds that their high concentration, growth and large turnover would have substantially skewed the wider analysis.[6] Additionally, subsectors dominated by public-sector employment were also excluded as they exhibit different competition dynamics to the private sector. For confidentiality reasons, the analysis also dropped subsectors with 20 or fewer firms. As such, concentration is likely to be higher than suggested by the report due to these omitted subsectors being some of the most concentrated ones.

8. Similar to the Resolution Foundation, Davies (2021) used the ONS's BSD to analyse concentration. The author utilised the HHI index to examine how concentration has changed from 1998 to 2018 in over 300 UK industries at the 4-digit level.[7]

9. As part of its state of competition report commission to the CMA, the Department for Business, Energy and Industrial Strategy (BEIS) (2020)[8] also analysed economy wide HHI, CR5, CR10, and CR15 concentration measures using ONS' Inter-Departmental Business Register (IDBR) data for the period of 2006 to 2018. To do this, BEIS first calculated these measures for 44

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[6] Across both wholesale of fuel subsectors, the report finds CR5 of 84% in 2015/16, which is double the average CR5 of all other subsectors (42%). Additionally, the authors stress that between 2003/04 and 2015/16, fuel wholesaling has increased its share of total revenue from 3% to 11%. Combined with their high market shares, the authors conclude that the inclusion of these subsectors would have resulted in more than twice as large concentration increases when averaged across the entire economy.

[7] Davies, S. (2021). Competition and Concentration: Charting the Faultines

[8] BEIS/HMT (2020), State of UK competition report: Commission to the CMA

sectors and then used a weighted average to obtain economy wide figures, with each sector being weighted by turnover.

10. The sectors analysed do not correspond exactly to SIC codes as BEIS aggregated certain SIC codes to ensure consistency with previous BEIS publications.[9] BEIS also published figures on churn,[10] firm entry and exit.

11. Aguda, Hwang, and Savagar (2019)[11] provide another assessment of concentration in the UK, using ONS' BSD data and focussing on the years between 1998 and 2018.[12] The authors exclude inactive firms, firms without employees or turnover data and firms with no reported entry/exit year.

12. The authors assess concentration in two different ways.

(a) First, they analysed the share of the top 5, top 10, top 20 and top 50 companies in the entire economy. They do this using a sample which includes firms from all available subsectors[13] and separately for a subsample which excludes firms from subsectors known to be poorly measured or where using turnover to indicate output might be problematic.

(b) Second, they analysed economy wide average CR5, CR10, CR20 and CR50 measures. To do this they first calculated these metrics at the sector level[14] and then combined these sector estimates to calculate weighted[15] averages at the economy-wide level.

13. Aguda, Hwang, and Savagar (2019) also assess the levels of firm entry and exit.[16]

14. Bajgar, Criscuolo & Timmis (2021) also examined the share of sales of the largest business groups.[17] They examined 13 countries using the Orbis

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[9] Ibid., Annex 2, Footnote 8 and Box 1

[10] Churn is the proportion of the firms in each industry which entered or left the market in each year.

[11] Aguda, O., Hwang, K.I., & Savagar, A. (2019), Product Market Concentration and Productivity in the UK

[12] To account for the SIC code changes introduced in 2007, the authors use ONS guidance to convert SIC 2003 codes to SIC 2007 codes. Additionally, turnover is deflated using ONS guidance.

[13] Contrary to the Resolution Foundation's definition of subsectors, Aguda, Hwang, and Savagar define broader, two-digit SIC codes as subsectors.

[14] We understand these sectors to be constructed by the authors and to sit above the two-digit level subsectors.

[15] These concentration ratios are weighted by sector turnover.

[16] Entry and exit are defined as follows: 'Entry is the first year that a firm is recorded as being active and records employees and turnover as non-zero or missing. Exit is the first year the firm is recorded as being inactive having being active the previous year or the first year a firm records turnover and employees as zero or missing.' Aguda, Hwang, and Savagar (2019, p8f).

[17] M. Bajgar, C. Criscuolo, & J. Timmis (2021). Intangibles and industry concentration: supersize me

dataset, described above, combined with the Worldscope dataset to obtain more information on publicly available firms.

15. The authors measured industry concentration as the share of the largest business groups in the total sales of that country and industry. The share of the eight largest firms was primarily used but the authors also tested the results with the top 4 and top 20 business groups. The top 8 entities in sales were not measured at the level of individual firms, but at the level of business groups. Firm sales were only aggregated to the business level within countries and industries.

16. There are other works that discuss concentration in the UK. These include Valletti, Koltay, Lorincz, and Zenger (2017)[18,19] They discussed concentration trends in the largest five economies in the EU using weighted average country/industry CR4 and HHI4[20] on Euromonitor data from 2010 to 2015.

17. Koltay, Lorincz & Valletti (2021) expanded upon this and again assessed concentration trends in the UK and the four largest European countries.[21,22] The authors used data collected by Euromonitor which combines the firm-level turnover value figures of the Orbis dataset, industry level aggregate data from Eurostat, as well as supplementary information on the firms' activity. The authors examined concentration from 1998 to 20019 using the methods below:

    (a) They examined the share of the four largest firms at the industry concentration indicator. Evidence on the evolution of profit margins was combined with this to aid in their analysis.

    (b) They examined how the share of high concentration industries within the total economy has changed to see whether concentration increases are focussed on high concentration markets.[23]

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[18] Valletti, T., Koltay, G., Lorincz, S., & Zenger, H., (2017), presentation titled: Concentration trends in Europe

[19] This work is currently being updated by the authors; the results have not yet been published at the time of writing.

[20] This is an HHI estimated based on just the data for the four largest firms of each industry. This would lead to a lower HHI than if all firms in an industry were included.

[21] G. Koltay, S. Lorincz, & T.M. Valletti (2021). Concentration and Competition: Evidence from Europe and Implications for Policy

[22] These are France, Germany, Italy and Spain. Together with the UK and prior to Brexit, these five countries were responsible for 80% of the EU GDP for 156 ISIC industry categories from 1998 to 2019.

[23] High concentration industries were defined as industries where the four largest firms account for at least 50% of turnover.

18. The authors excluded industries which were heavily influenced by public sector involvement and those under the 'other' category which they described as a 'catch all industry'.[24]

19. The Social Market Foundation (2017)[25] use a more disaggregated approach, analysing concentration in ten consumer markets that together are estimated to account for 40% of total consumer expenditure in the UK.[26] The concentration measures used are HHIs, CR1 and CR4. Given this study focusses on consumer markets rather than industry sectors or subsectors, it does not draw on one single data source. Rather, it combines market specific sources. The timeframe goes as far back as 2000 for certain consumer markets, with other markets being tracked from a later point. Most markets are assessed until 2016, with two being assessed until 2017

20. Papers focussed on concentration in Europe, the US or both have generally used similar metrics (or variations thereof), albeit with different data sources. The results of these papers are considered at paragraphs 2.35 to 2.40.

CMA data and methodology

21. This analysis primarily uses the Business Structure Dataset (BSD), maintained by the ONS. This dataset includes all businesses in the UK which are registered in the VAT[27] or PAYE[28] taxation system (approximately 50% of UK businesses by count, and over 99% of UK business turnover).[29] The dataset includes public sector entities, such as NHS[30] trusts and local authorities, which have been excluded from the analysis.

22. This dataset classifies firms according to the primary industry they operate in, according to the SIC system. This system divides the activities of business into 21 sectors (denoted by letters), 88 2-digit divisions and 615 4-digit classes (some of which are further divided into 191 5-digit subclasses). Table A.1 shows an example from this classification system.

[24] The industries excluded were public administration, education, health and social work.

[25] Social Market Foundation (2017), Concentration not competition: the state of UK consumer markets

[26] Based on ONS Family spending data for 2015/16. These markets, which include mortgages, groceries etc, are thus some of the most important markets to consumers, significantly impacting their welfare according to the Social Market Foundation.

[27] Value Added Tax

[28] Pay As You Earn

[29] The BSD is described in detail in its documentation, available on the UK Data Service website.

[30] National Health Service

Table A.1: Example of SIC classification

Sector	C	Manufacturing
2-digit division	13	Manufacture of textiles
3-digit group	139	Manufacture of other textiles
4-digit class	1393	Manufacture of carpets and rugs
5-digit subclass	13931	Manufacture of woven or tufted carpets and rugs

23. Our analysis calculates market structure metrics primarily at the 4-digit level. We focus on the 4-digit industry level, as this is the greatest level of granularity possible over a 1998 to 2018 time series (the longest possible span with the BSD data).[31] Where we consider our metrics at the sector and whole economy level these are created in most cases by aggregating metrics of the underlying 4-digit SIC codes that they contain.

24. However, we note that even the 4-digit SIC codes are unlikely to match up to any economic markets which may be defined by the CMA in, for example, a market review, merger inquiry or Competition Act 1998 investigation. In particular, when defining the relevant market as part of casework the CMA considers both the relevant product market and relevant geographic market and:

    (a) 4-digit SIC codes are likely to be far broader than any 'product market' the CMA would define in any case.[32] For example, 'Manufacture of pharmaceutical preparations' is a single 4-digit SIC code despite consisting of a vast number of individual products which are not substitutable for each other; and

    (b) data within the BSD is only available at the national level, but geographic markets are not necessarily national and can be either local or international. For example, it might be the case for some products that bricks-and-mortar retailers would only compete with other bricks-and-

[31] Methodological problems are caused by the changes to the UK SIC system which happened in 2003 and 2007. Converting pre-2007 SIC codes to the 2007 SIC code system can only be done at the 4-digit level.
[32] Following the OFT (2004) Market Definition guidance, the CMA attempts to define product markets as the narrowest possible market, or group of products, over which a hypothetical monopolist could profitable sustain supra competitive prices – also called a hypothetical monopolist test. It should be noted that 'product' can refer to either a good, service or property right.

mortar retailers if they are both within a reasonable travelling distance of each other for consumers.[33]

25. Where results are presented at a sector level, we present two sets of sectors separately to avoid there being too many lines on a single chart, making it unreadable. Higher total-turnover sectors (turnover above the median, a proxy for those of most economic importance) are presented on one chart and lower total-turnover sectors are presented on another. Also, we omit some non-market, government dominated, and heavily regulated industries and combine some sectors that contain similar industries.[34] The list of sectors used and how they are split is in Table A.2.

Table A.2: Higher- and lower-turnover sectors

Higher-turnover sectors	Total turnover, 2021, £bn
Wholesale and retail trade; repair of motor vehicles and motorcycles	1,551
Finance and Insurance	1,447
Professional and support services	696
Manufacturing	637
Construction	349
Information and communication	303

Lower-turnover sectors	Total turnover, 2021, £bn
Transport and storage	221
Other services	127
Accommodation and food services	119
Real estate activities	84
Agriculture, forestry and fishing	48
Mining, quarrying and utilities	37

Source: CMA analysis of ONS BSD data
Note: Other services includes Arts, entertainment and recreation, and other services (including the repair of goods, and personal services). Professional and support services includes Professional, scientific and technical and Administrative and support services, 'Government, education, health and defence' – which included the SIC sectors for Public administration and defence; compulsory social service, Education, and Human health and social work sectors – has been excluded from the table and from charts in this report because only a small proportion of this SIC code represents market activity by private businesses. Electricity and water supply have been excluded because highly regulated.

[33] Retailers may often compete both at the local level and the national level. As set out in CMA (2017), Retail mergers commentary, the CMA assesses at what geographic scope competition is taking place. In certain markets, the lines between local and national competition are blurred, with certain aspects being decided centrally, while others are set locally. For example, in Ladbrokes/Coral the CMA found that betting odds were decided nationally, while prices were based on local competition.
[34] These combinations of SIC sectors follow those used in House of Commons Library (2019), Industries in the UK, Research Briefing

Findings

26. Concentration is perhaps the most widely used competition indicator in academic research and by competition authorities and other organisations internationally. The existing work by the Department for Business, Energy and Industrial Strategy (BEIS) and the Resolution Foundation (see Chapter 2 of the main report) focussed on concentration as the main metric.

27. Estimating concentration within individual markets is an intuitively simple way to measure the level of competition across an economy. However, there are some caveats to note with the measurement of industry concentration that we have undertaken, and the underlying causes of observed changes industry concentration may be unclear.

28. Concentration metrics do not measure market power directly; they are one step removed. For example, an increase in concentration can be the result of a firm using anti-competitive behaviour to gain market share and exclude a rival, but it can also be the result of fierce competition, with less efficient firms being forced to leave the market.

29. We must rely on data gathered at an industry level and use these as stand-ins for economic markets. As competition occurs at a market level, changes in an industry's relative market composition may alter aggregate measures of competition without reflecting any changes in competition in individual markets.[35]

30. The mismatch between industry sectors defined by the SIC system and economic markets can be significant.[36] Similarly, only national data is available on business turnovers whereas economic markets may be regional or local. For example, if a retail chain entered multiple local areas then there may be an increase in the measured national concentration as it is likely that the retail chain would make more sales nationally. However, there may be no increase (and possibly a decrease) in the concentration of any local markets it enters into as existing retail stores in those local areas face an additional competitor.[37]

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[35] For example, a SIC code that includes multiple economic markets may conceal an increase in concentration in one of these markets by aggregating it with other markets where concentration did not significantly change.
[36] Werden, G. J., & Froeb, L. M. (2018), Don't Panic: A Guide to Claims of Increasing Concentration, *Antitrust Magazine* examine the defined markets in US Department of Justice merger investigations during the 1980s and find that 17 of the 47 defined markets accounts for less than 1% of the commerce of the industry code they are in.
[37] Rossi-Hansberg, E., Sarte, P. D., & Trachter, N. (2018), Diverging trends in national and local concentration (No. w25066), *National Bureau of Economic Research*

31. Enterprises may perform multiple activities which are covered by multiple SIC codes. Despite this, all of an enterprise's revenues must be ascribed to a single SIC code – the one which is most important in terms of revenue. Some enterprises on the BSD list a secondary SIC code, but this is inconsistent and there is no way of judging how much of the enterprise's revenue should be ascribed to the secondary SIC code, so we have not attempted to do this. This data issue may lead to concentration being overestimated across the economy, as firms' revenues will be overestimated in their primary SIC codes, and their secondary SIC codes will be recorded as containing fewer firms than they in fact do.

32. Our concentration metrics as presented in Chapter 2 are based on domestic production, which means that, in an industry of international scope, they will provide a misleading view of the actual structure of the market. When charting changes in the estimated level of concentration over time, this poses a particular problem – many markets in developed countries, particularly those for manufactured goods, have seen increasing levels of imports and the closure of domestic manufacturers. This trend will cause levels of industry concentration to appear to grow as they are based on measuring an increasingly small section of the true industry, while the actual level is unknown.[38] We assess this problem in Chapter 3.

Sector-level concentration

33. There are individual trends apparent at a sector-level (ie when we aggregate all the individual 4-digit SIC codes in a specific sector) that differ somewhat from the whole economy picture. It should also be reiterated that 'natural' levels of concentration in different sectors will vary due to differing cost structures and other parameters. Therefore, we focus on trends in the concentration of particular industries over time, and differences in these trends between sectors.

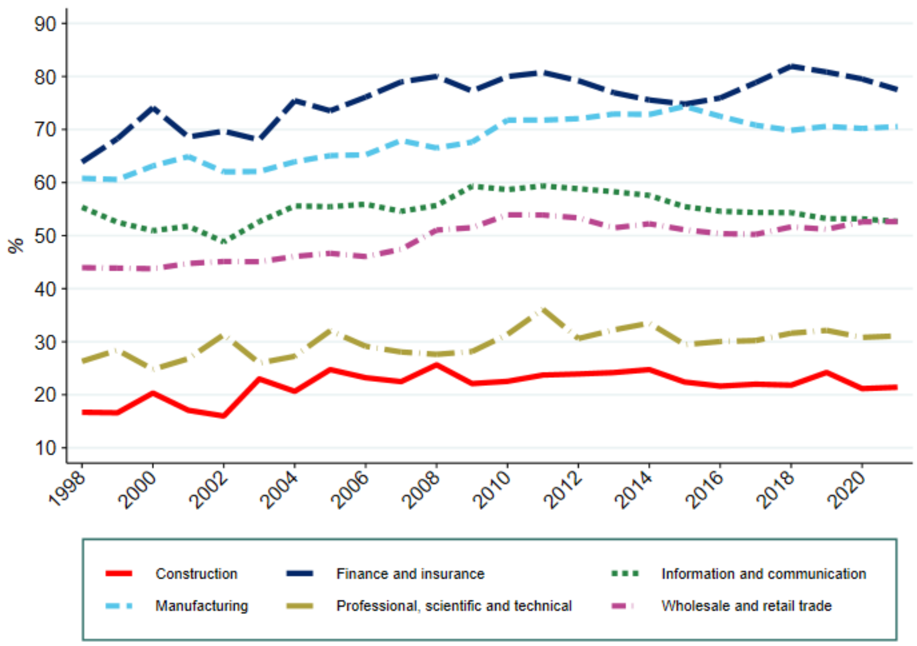
34. Changes in the structures of industries over time (while the definitions of SIC industries stay the same) mean that direct comparisons of concentration level across long periods of time may be misleading, as the SIC system will become poorer at describing the current activities of businesses as time passes. However, the direction and magnitude of change from one year to the next is likely to be a reliable indicator of changes taking place.

[38] A similar caveat applies in industries where a large proportion of UK output is exported.

C10

35. Figure A.1 shows the average C10, weighted by turnover, within each sector for the six sectors in the UK economy with the highest total business turnover[39] for the period 1998 to 2021. These sectors account for an annual average of 82% of the combined turnover of firms in the BSD.

Figure A.1: Turnover-weighted mean C10 within each high turnover sector



Source: CMA analysis of ONS BSD data
Note: Data issues mean that figures for 1997 have been dropped and figures for 2007 may be anomalous. C10 is calculated at 4-digit SIC code level and then aggregated to sector level using a weighted average by total firm turnover.
Professional and support services includes both Professional, scientific and technical activities, and Administrative and support service activities. Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example Activities of religious/political/trade union organisations, and Activities of households as employers of domestic personnel. The 4-digit industry Wholesale of solid; liquid and gaseous fuels and related products is also excluded as its turnover disproportionately affects our results.

36. Figure A.1 shows that concentration has increased over the period for most of these key sectors. The sectors differ in the degree to which they become more concentrated prior to the financial crisis, with concentration stabilising across most sectors following that point. It is unsurprising these trends mirror the overall picture given these sectors account for an annual average of 82% of the combined turnover of firms in the BSD. Finance and insurance[40] stands out as a sector where concentration increased the most in the run-up to the

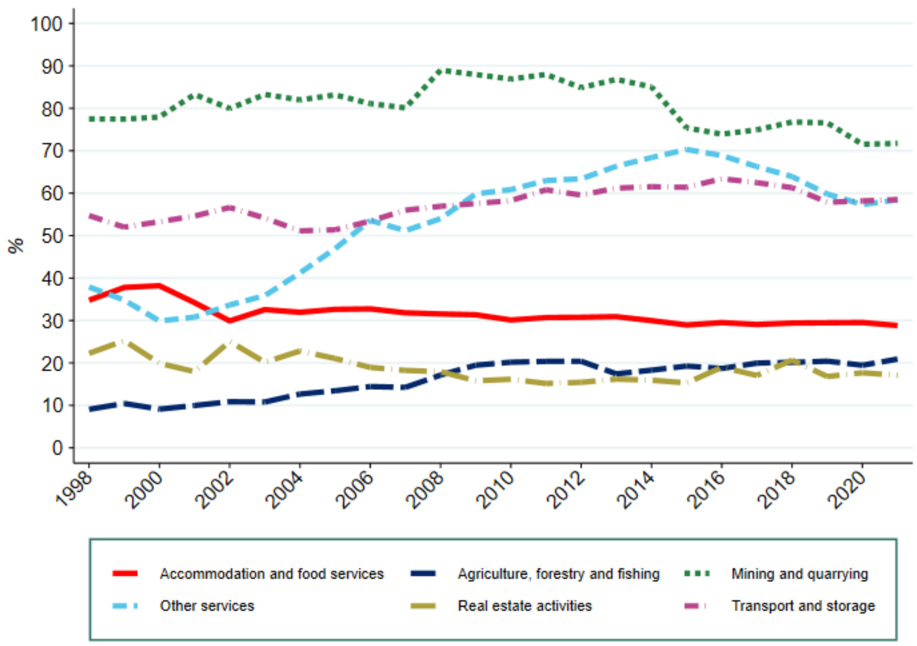
[39] Details and charts on the other seven sectors may be found in Appendix A paragraph 35 onwards.

[40] Care should be taken in interpreting the Finance and insurance figure as the recorded turnovers of financial firms will depend heavily on the exact type of business the firm is doing and will represent a different concept to the turnover of a manufacturing or retail firm.

financial crisis from less than 64% in 1998 to more than 80% in 2011, as does Manufacturing whose C10 increased from approximately 61% in 1998 to 74% in 2015.

37. Figure A.2 shows the average C10, weighted by turnover, within each sector for the lower-turnover sectors. This second set of sectors account for 11% of the combined turnover of firms in the BSD.

Figure A.2: Turnover-weighted mean C10 within each low turnover sector



Source: CMA analysis of ONS BSD data
Note: Data issues mean that figures for 1997 have been dropped and 2007 figures may be anomalous. C10 is calculated at 4-digit SIC code level and then aggregated to sector level using a weighted average by total firm turnover.
Other service activities includes Arts, entertainment and recreation, and Other service activities (including the repair of goods, and personal services). Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example Activities of religious/political/trade union organisations, and Activities of households as employers of domestic personnel.

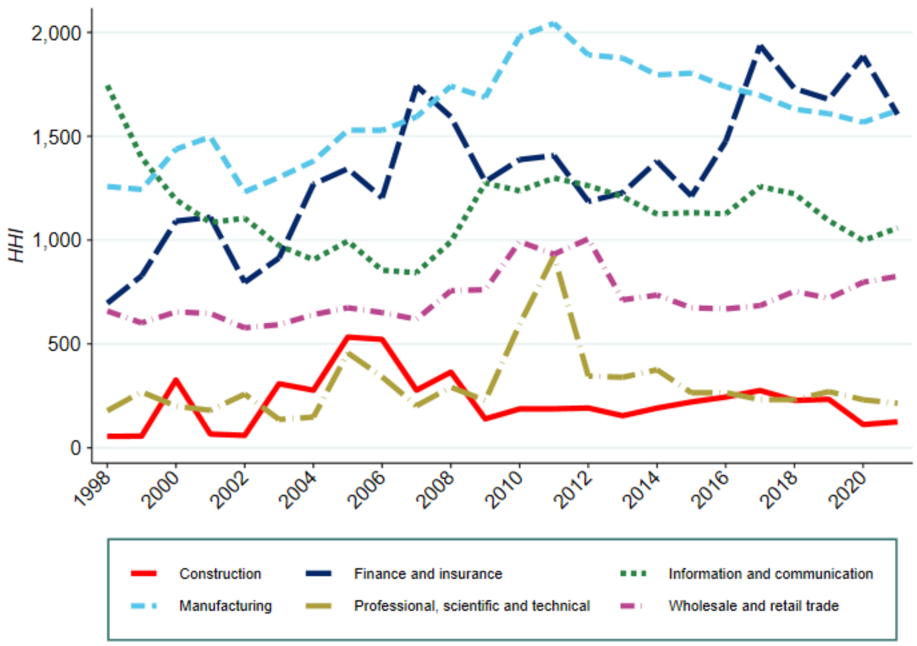
38. Some of these sectors exhibit similar patterns to that described above as they show a relative peak around 2010 (for example Mining and quarrying). In contrast, in some sectors concentration increases significantly throughout the period (Transport and storage, Other services,[41] and Agriculture, forestry and fishing) while others become less concentrated over the period (Accommodation and food services, and Real estate activities).

[41] 'Other services' principally includes Arts, entertainment and recreation, and personal services.

HHI

39. Figure A.3 shows the average HHI, weighted by turnover, within each of the high-turnover sectors. The HHI is more volatile because a small change in market share implies a quadratic impact on its value. Therefore, we focus on the long-term trends rather than the short-term fluctuations.

Figure A.3: Turnover-weighted mean HHI within each high turnover sector

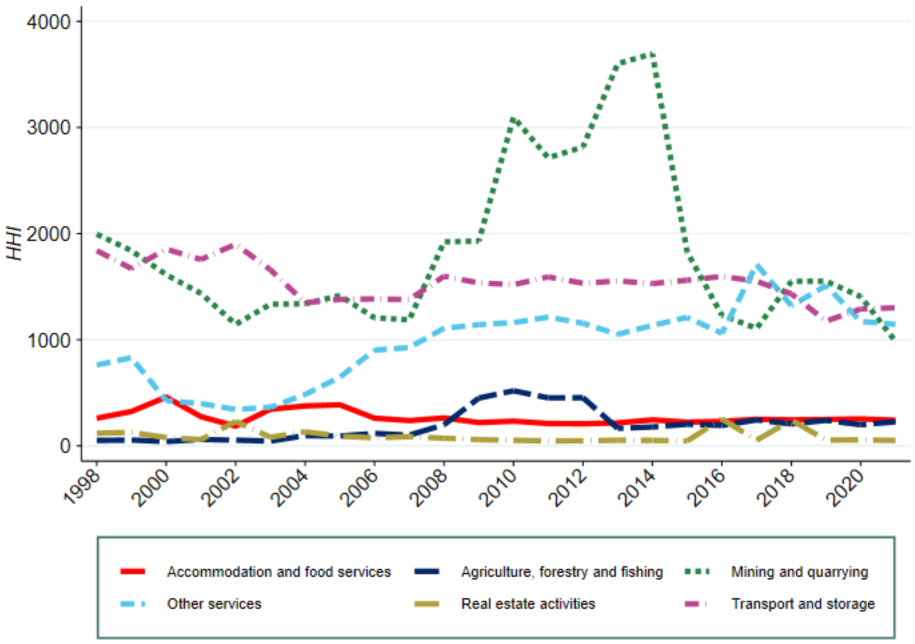


Source: CMA analysis of ONS BSD data
Note: Data issues mean that figures for 1997 have been dropped and figures for 2007 may be anomalous. C10 is calculated at 4-digit SIC code level and then aggregated to sector level using a weighted average by total firm turnover.
Professional and support services includes both Professional, scientific and technical activities, and Administrative and support service activities. Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because highly regulated. The 4-digit industry Wholesale of solid; liquid and gaseous fuels and related products is also excluded as its turnover disproportionately affects our results.

40. Figure A.3 shows consistent results with the C10 for some sectors, but not for all. Similarly to Figure A.1, most sectors display a relative peak in the early 2010s, after the financial crisis (eg Manufacturing, Wholesale and retail trade, and Professional, scientific and technical activities). However, the HHI shows a different pattern for Finance and insurance whose concentration more than doubled since 1998.

41. Figure A.4 shows the average HHI, weighted by turnover, within each sector for the lower-turnover sectors.

Figure A.4: Turnover-weighted mean HHI within each low turnover sector



Source: CMA analysis of ONS BSD data
Note: graph excludes Mining and quarrying because of small sample size.
Data issues mean that figures for 1997 have been dropped and 2007 figures may be anomalous. HHI is calculated at 4-digit SIC code level and then aggregated to sector level using a weighted average by total firm turnover.
Other services includes Arts, entertainment and recreation, and Other services (including the repair of goods, and personal services). Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because highly regulated. We have also excluded several non-market 4-digit SIC industries, for example Activities of religious/political/trade union organisations, and Activities of households as employers of domestic personnel.

42. Transport and storage display a declining HHI, whereas Other services increase significantly over the considered period. Accommodation and food services, Real estate activities, and Agriculture, forestry and fishing have low and relatively stable levels of HHI.[42]

[42] We are cautious in the interpretation of trends for Electricity and water supply and Mining and quarrying because their levels are very erratic due to the small sample size. Therefore, we do not present their graphs here.

Appendix B: Adjusted concentration

43. Chapter 2 and Appendix A noted that typical concentration metrics (C10 and HHI) do not account for common ownership – owners having control in multiple companies – or international trade.

44. Chapter 3 gave an overview of the economic theory that suggests these are shortcomings of traditional concentration measures, and the existing evidence on their effect on concentration and competition. It then outlined our analysis aiming to use existing data sources on common ownership and international trade to understand how they might be affecting concentration in the UK.

45. This appendix first looks at existing studies on common ownership and competition in more depth, then provides a detailed description of our data sources and methodology for incorporating common ownership into calculations of the C10 and HHI. It also provides an extended review of existing research on international trade and competition.

Existing studies on common ownership and competition

46. As discussed in Chapter 3, traditional economic thinking proposes that firms will each act in their own interests and maximise their own profits. The common ownership hypothesis suggests instead that if firms have overlapping ownership, then owners may prefer that firms internalise, to some extent, the impact of their decisions on the profit of their competitors. This interdependence of firms' incentives can reduce competition.

47. The two central questions around which research has developed in this area are: do commonly owned firms have the incentive to soften competition? Is there any empirical evidence of this?

48. Theoretical work has addressed the former question, whilst empirical work deals with the latter. In this section, we discuss the highlights of the literature so far.

Theoretical models

49. Theory attempts to shed light on whether commonly owned firms have the incentive to compete less fiercely. The main mechanism of harm proposed by this argument is best formalised by Hansen and Lott (1996) who built an economic model to demonstrate that when firms maximise the weighted

average of their owner's portfolio profits (rather than maximising strictly their own profits), a greater degree of common ownership reduces competition.[43]

50. Several other studies provide economic models and examples that show that common ownership leads to anti-competitive incentives. The underlying logic is similar across these studies: common ownership leads firms to internalise the consequences of their actions on rivals' profits to some extent. It is generally understood that higher common ownership means a greater internalisation of rival's profits and thus weaker competition.

51. A few examples of such papers include:

(a) Rubenstein and Yaari (1983) provide examples to show that investors with holdings in separate firms are incentivised to buy shares in other firms to reduce competition.[44] The mechanism described is one where acquiring shares in rival firms and forcing them to compete less aggressively implies that an owner will see higher portfolio profits through the recoupment of profits that would have been diverted to competitors. Similarly, Macho-Stadler and Verdier (1991) and Bernheim and Whinston (1985) also argued that managers with cross ownership holdings are incentivised to compete less fiercely.[45]

(b) Rotemberg (1984) produces the benchmark result that when identical shareholders are fully diversified (ie when all shareholders hold exactly the same portfolio and hold equal shares in all firms) competitive ferocity is lost and the monopolistic outcome prevails.[46] This is essentially the most extreme example of what Hansen and Lott (1996) described. In this case, all firms will weight each other's profits equally to their own and all firms will maximise the same profit function. Thus, it is essentially the monopoly outcome.

(c) Reynolds & Snapp (1985) arrive at the same conclusion that common ownership is anticompetitive, but add that this is particularly true in industries with high barriers to entry.[47] Such industries mean that new

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43 Hansen, R., and Lott, J. 1996. Externalities and Corporate Objectives in a World with Diversified Shareholder/Consumers. *The Journal of Financial and Quantitative Analysis.* Vol 31, No. 1.

44 Rubenstein, A., & Yaari, M.1983. The competitive stock market as a cartel maker: Some examples. *Theoretical Economics Paper Series, London School of Economics.*

45 Macho-Stadler, I., & Verdier, T. 1991. Strategic managerial incentives and cross ownership structure: A note. *Journal of Economics,* Vol 53 No. 3, pp. 285-297. Bernheim, D., & Whinston, M. 1985. Common marketing agency as a device for facilitating collusion. *The RAND Journal of Economics.* Vol 16, No. 2, pp. 269-281.

46 Rotemberg, J. 1984. Financial transaction costs and industrial performance. *Working paper MIT Sloan School of Management.* WP 1554-84.

47 Reynolds, R., & Snapp, B. 1985. The competitive effects of partial equity interests and joint ventures. *International Journal of Industrial Organization.* Vol 4, Issue 2, pp. 141-153.

entrants cannot enter after observing the high profits of incumbents (arising due to reduced competition from common ownership) and thus these anticompetitive practices could be more easily sustained without threat of an entrant undercutting the incumbents.

52. Another suggested mechanism of harm is that commonly owned firms may find it easier to collude due to increased communication arising from having similar ownership. Several papers discuss this possibility, but this is outside the scope of this literature review.

Empirical Studies

53. Empirical studies aim to investigate whether firms act on any incentive to reduce competition that arises from common ownership. Empirical papers are less cohesive in their findings than theoretical work. While some studies found a negative impact of common ownership on competition, others debate the robustness of such findings and provide a more nuanced picture.

The MHHI

54. Much of the modern empirical works uses a modified version of the HHI (the so-called MHHI) as the measure of common ownerships impact. For this reason, we precede discussion of the empirical literature with an overview of the MHHI to aid understanding of the following section.

55. The MHHI was first introduced by Bresnahan & Salop (1985) to measure the degree to which joint ventures might impact competition.[48] However, the version of the MHHI which has become the most used in the modern literature was a generalisation of this work by O'Brien & Salop (2000).[49]

56. The MHHI is a modified HHI, which considers not only classic concentration as discussed in Chapter 2, but also adds an additional component which captures the extra concentration arising from ownership structure. It can be expressed as follows:

$$MHHI = \sum_k \sum_j \left(\frac{\sum_i \gamma_{ij} \beta_{ik}}{\sum_i \gamma_{ij} \beta_{ij}} \right) s_k \, s_j$$

[48] Bresnahan, T, and Salop, S. 1986. Quantifying the competitive effects of production joint ventures. *International Journal of Industrial Organization.*
[49] O'Brien, D., and Salop, S. 2000. Competitive effects of partial ownership: financial interest and corporate control. *Social Science Research Network.*

Here, s_k represents the market shares of firm *k*, s_j represents the market shares of firm *j*, γ_{ij} represents the extent of control owner *i* has over firm *j*'s decision making, and β_{ik} represents owner *i*'s shareholding in firm *k*.

This expression can be decomposed as follows, to allow for clearer understanding of what MHHI captures:

$$MHHI = HHI + MHHI\,delta$$

It is proposed that MHHI delta captures the extra concentration arising due to common ownership. The higher delta is, the more concentrated the market is as a result of common ownership. Assuming that concentration is an appropriate measure of competition, this means a higher delta means lower market competition.

57. O'Brien (2017) criticises the MHHI as a variable able to capture any effect of common ownership on prices, and thus casts scrutiny on any paper whose results depend on this measure – this includes some of the most seminal papers in the literature, as we will see in the next section.[50] The paper presents an argument that price-concentration analysis does not have any grounding in economic theory and as a result the outcomes in price-concentration analysis have no clear interpretation. Given the MHHI measures the component of concentration arising due to common ownership, this argument is a direct rebuttal of the credibility of MHHI in measuring the impact of common ownership on price. O'Brien shows that there is indeed a spurious relationship between MHHI (concentration) and price. It is shown that changes in MHHI that yield a higher price may increase or decrease concentration, and so for a given value of MHHI it is possible to see a competitive or an anticompetitive price – so MHHI is not a reliable indicator of competition.

58. We now turn to the main empirical studies on common ownership. Since they tend to focus on a singly industry, we divided our discussion accordingly.

The Airline Industry

59. Azar et al (2018) investigate the competitive impact of common ownership on prices in the American airline industry.[51] The paper presents evidence to suggest that – based on HHI merger guidelines – common ownership as measured by MHHI delta yields increases in concentration ten times greater

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[50] O'Brien, D. 2017. Price concentration analysis: ending the myth and moving forward. *SSRN.*

[51] Azar, J. Schmalz, M. & Tecu, I. (2018) Anticompetitive effects of common ownership, *The Journal of Finance*

than those which antitrust authorities consider likely to reduce competition in the context of merger analysis. Using an econometric approach, it also finds that evidence to suggest that common ownership increases prices in the US airline industry. Similarly, Park and Seo (2018) find evidence of a positive relationship between price and common ownership in the airline industry.[52]

60. Several papers wrote responses to Azar et al (2018), challenging the results. We summarise some of these. For brevity, in the following discussion Azar et al (2018) is referred to as AST:

61. Dennis et al (2018) argues that AST's results that higher common ownership yields higher prices is due to variation in market shares and not common ownership.[53] Gilje et al (2019) provide evidence which supports this argument.[54] It should be noted that AST respond to this criticism and cite differences in data sets, outlining that Dennis et al (2018) use a version of AST's data with notably different summary statistics, and that this drives the different results.

62. Kennedy et al (2017) replicate AST's analysis but replace the concentration-based measures of common ownership (MHHI) with a purer measure of ownership.[55] This method removes the problem of market shares influencing the observed relationship between price and common ownership. Under this methodology, there is no evidence that common ownership leads to increased prices in the airline industry. The authors are able to closely construct AST's dataset and replicate most of their results, so the different outcomes are not driven by stark variations across datasets as AST argued about the Dennis et al (2018) critique. Moreover, O'Brien (2017) mentions that the method employed by Kennedy et al (2017) avoids the criticism of price-concentration analysis – discussed in paragraph 15.

63. Egland et al (2019) argue that the results of AST are contingent on the precise specification of the model employed by the authors and that the results are not robust to other assumptions.[56] For example, it explains that AST assume an investor's interest in a firm is equal to that investors fraction of holdings in the firm – both voting and non-voting. The authors argue that

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[52] Park, A., and Seo, K. Common ownership and product market competition: Evidence from the U.S. airline industry. *Korean Journal of Financial Studies.*

[53] Dennis, P., Gerardi, K., and Schenone, C. 2018. Common ownership does not have anti-competitive effects in the airline industry. *SSRN.*

[54] Gilje, E., Gormley, T., and Levit, D. 2019. Who's paying attention? Measuring common ownership and its impact on managerial incentives. *Journal of finance.*

[55] Kennedy, P., O'Brien, D., Song, M., and Waehrer, K. 2017. The competitive effects of common ownership: economic foundations and empirical evidence. *SSRN.*

[56] Egland, M., Hearey, O., Schatzki, T., and Verbeck, C. Reassessing Common Ownership: Corrections to Azar, Schmalz, and Tecu (2018). *SSRN.*

this is inappropriate in the case of asset managers who do not own the underlying assets and only manage the shares for clients – in essence making a principle-agent problem argument. This study shows that amending this alters AST's results and renders the relationship between MHHI delta and price insignificant. Thus, the paper argues that there is no evidence that common ownership is anticompetitive in the airline industry.

The Banking Industry

64. Azar et al (2016) introduce the GHHI as a variation of MHHI which accounts for not only common, but also cross, ownership.[57] In this context, common ownership is when firms have a shared third party investor with shareholdings in both, while cross ownership is where firms directly hold shares of each other. The GHHI is used by Azar et al (2016) to study the relationship between price and ownership in the banking industry. As with the MHHI, this can be decomposed into:

$$\text{GHHI} = \text{HHI} + \text{GHHI delta}$$

So that the GHHI delta is the difference between GHHI and HHI, and thus captures the component of concentration arising as a result of common and cross ownership.

65. The question investigated is whether the different ownership of banks had an impact on competitive behaviour. This was explored by studying whether the GHHI would outperform the HHI in explaining variation in the price of banking products. The study finds that GHHI was a more robust predictor of market outcomes than the HHI and the authors provide evidence to support that there might exist a causal relationship between prices of banking products and GHHI. However, as the GHHI is also a measure of concentration, it too is subject to O'Brien's (2017) critique.

66. Avoiding, the O'Brien (2017) critique by replacing concentration measures with a more direct measure of ownership, Gramlich and Grundl (2016) also study the banking industry.[58] The major outcome of the results is that there is no clear evidence on the impact of common ownership on competitive conduct. This work found mixed signs and low magnitudes of any observed effects – in some cases this work even found evidence of (small) pro-competitive effects of common ownership on market outcomes – a stark contrast to the evidence presented by concentration-based measures.

[57] Azar, J., Raina, S., & Schmalz, M. 2016. Ultimate ownership and bank competition. *SSRN.*
[58] Gramlich, J., & Grundl, S. 2016. Estimating the competitive effects of common ownership. *FEDS Working Paper No.2017-29.*

Other Industries

67. Nain & Wang (2016) investigate the relationship between common ownership and product market competition using a relatively large cross industry sample of manufacturing firms in the US.[59] This work finds that after an acquisition of a minority shareholding in a rival, prices (measured by real producer price index, or RPPI, a measure of price faced by producers) increased by 2% and price-cost margins by 0.7%. It is also shown that the anticompetitive effects of partial equity ownership are greater in industries with higher barriers to entry – in line with the findings of Reynolds & Snapp (1985). The paper thus provides the first large sample evidence in support of the common ownership hypothesis.

68. Koch et al (2020) also look at the manufacturing sector and investigate whether common institutional ownership across firms in an industry has any impact on the prevailing level of product market competition.[60] The authors investigate this using a variety of industry classifications, several measures of common ownership and profitability, as well as allowing for consideration of non-price competition. Overall, the results show that there is no significant relationship between common ownership and product market competition.

69. The key difference between these two papers is that Nain and Wang (2016) look at 'partial mergers' (the acquisition of minority stakes), whereas Koch et al (2020) look at common ownership by an institutional investor. Koch et al (2020) suggest that the differences in results are due to the different impact that partial mergers and common ownership by institutional investors have on market outcomes.

70. Backus et al (2021) study whether data on pricing behaviours in the ready-to-eat cereal industry best supports joint or own profit maximisation.[61] There are several aspects of the ready-to-eat cereal industry which the authors propose make it a suitable candidate for this analysis. Firstly, it is an oligopolistic industry dominated chiefly by four major firms, and these firms all have considerable variation in ownership structure – which makes it an interesting industry for a study on the impact of ownership. The authors also note that there are many transactions in the ownership space which allows for the study of intertemporal variation in ownership on product market interactions across

[59] Nain, A., & Wang, Y. (2016) The product market impact of minority stake acquisitions, *Management Science.*

[60] Koch, A., & Panayides, M., & Thomas, S. (2021) Common ownership and competition in product markets, *Journal of Financial Economics*

[61] Backus, M, Conlan, C., & Sinkinson, M. (2021) Common ownership and competition in the ready-to-eat cereal industry, *National Bureau of Economics*

the firms. Overall, Backus et al (2021) find no evidence that common ownership impacts competitive conduct.

71. He & Huang (2017) provide evidence of a causal relationship between common institutional ownership and reduced product market competition.[62] The authors used a variety of metrics to measure common ownership and market shares as the main measure of product market competition. The paper offers support that common ownership is anticompetitive. The authors look at firms with common stocks traded on NYSE, NASDAQ and AMEX between 1980-2014 and assign industry using 4-digit SIC codes, and they analyse the impact of common ownership across industries. This work is one of few which considers several industries in the analysis. However, the main limitation is that their main metrics of common ownership does not vary across level of common ownership.

CMA analysis

72. Common ownership is when shareholders own stakes in multiple companies. When this occurs in the same or similar market or industry, businesses might have reduced incentives to compete in order to maintain high profits across the commonly owned businesses.

73. To evaluate if and how common ownership might affect competition in the UK economy, we exploited two datasets:

    (a) The Inter-Departmental Business Register (IDBR), and administrative record of every business in the UK that is PAYE or VAT registered; and

    (b) Companies House (CH) data on all registered UK companies - irrespective of their PAYE or VAT registration - and their ‘Persons with Significant Control’ (PSC).

74. This Appendix provides more detail on both these data sources, their coverage, and how we used them to estimate adjusted concentration measures in Chapter 3 of the main State of Competition 2022 report.

75. We note that the examination of these datasets and the discussion of concepts of ownership, control, links and/or independence are not intended to reflect the approach taken by the CMA to control or material influence in the context of merger control. Our use of these terms in this report is distinct from how they are used for the purposes of merger control under the Enterprise Act

[62] He, J., and Huang, J. 2017. Product market competition in a world of cross-ownership: evidence from institutional blockholdings. *Review of Financial Studies. No.30*.

2002. For the avoidance of doubt, the CMA's approach to control and material influence in establishing whether a relevant merger situation exists is set out in its published guidance on jurisdiction and procedure,[63] and nothing in this report should be interpreted as relevant to the basis for, or the assessment of, control or material influence under the Enterprise Act 2002.

The Inter-Departmental Business Register

76. The IDBR contains information on every business in the UK that is PAYE or VAT registered. As a result, it does not cover many small businesses that do not meet these criteria. It categorises businesses into three categories according to the EU Regulation on Statistical Units (EEC 696/93).[64] In "bottom-to-top" hierarchical order these are:

(a) local units: 'The local unit is an enterprise or part thereof (eg a workshop, factory, warehouse, office, mine or depot) situated in a geographically identified place. At or from this place economic activity is carried out for which – save for certain exceptions – one or more persons work (even if only part-time) for one and the same enterprise.'[64]

(b) enterprises: 'The enterprise is the smallest combination of legal units that is an organisational unit producing goods or services, which benefits from a certain degree of autonomy in decision-making, especially for the allocation of its current resources. An enterprise carries out one or more activities at one or more locations. An enterprise may be a sole legal unit.'[64]

(c) enterprise groups: 'An enterprise group is an association of enterprises bound together by legal and/or financial links. A group of enterprises can have more than one decision making centre, especially for policy on production, sales and profits. It may centralise certain aspects of financial management and taxation. It constitutes an economic entity which is empowered to make choices, particularly concerning the units which it comprises.'[64]

77. Local units report their turnover as part of a reporting unit, and this is attributed to an enterprise. These enterprises can then be part of a wider enterprise group. Although the IDBR does not have extensive information on shareholdings or control, the identification of enterprise groups does allow our

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[63]CMA (2014), Mergers: Guidance on the CMA's jurisdiction and procedure, paragraphs 4.12-4.41
[64] Council Regulation (EEC) No 696/93 of 15 March 1993 on the statistical units for the observation and analysis of the production system in the Community. (1993). *Official Journal*, L 76, 1-11. CELEX: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:31993R0696

analysis – both on common ownership and concentration more generally – to account for some ownership links between enterprises.

78. Figure B.1 shows a simple tabular example of the IDBR hierarchy. In our analysis – both on common ownership and concentration generally – we define “businesses” as enterprises that are part of the same enterprise group within a 4-digit SIC industry. We make this choice because we are interested in using SIC industries to approximate markets.

Figure B.1: an example of the IDBR business hierarchy

Enterprise Group	**Brown**	**Smith and Jones Holding**					
Enterprise	**Brown**	**Smith**				**Jones**	
Local Unit	**Brown Plant**	**Smith North**	**Smith South**	**Smith East**	**Smith West**	**Jones North**	**Jones R&D**
Reporting Unit	**A**	**B**		**C**	**D**	**E**	

Source: Business Structures Database User Guide.

79. The IDBR is updated continuously throughout the year. We obtained a snapshot current in September 2021. More detail on the IDBR can be found in the Business Structures Database User Guide.

Companies House data on persons with significant control

80. Companies House maintains a register of all limited companies or limited liability partnership companies in the UK. It collects information about companies (such as ownership, accounts, etc) and makes this data available to the public.

81. Companies are registered with CH irrespective of whether they operate a PAYE scheme or are registered for VAT. At the same time, certain business structures, such as sole traders, do not need to be registered with CH, while they do need to be VAT registered. As a result, CH covers a different set of businesses than IDBR.

82. Since the Enterprise and Employment Act 2015, all UK companies have been required to record with CH the details of those who hold significant control in their company. “Significant control” is defined as:

‘persons, both legal and natural who, directly or indirectly: (a) own more than 25% of the shares in a company: (b) control more than 25% of the voting rights in a company; (c) hold the right to appoint or remove the majority of the board of directors of the company; or (d) otherwise have the right to exercise, or actually exercise, significant influence or control.'

83. We obtained two snapshots of the CH data: a register snapshot and a PSC snapshot. Both are current to December 9th, 2021. The register snapshot contains information on all the roughly 5 million active companies registered at CH at the time of the snapshot. The PSC snapshot contains all of the approximately 6.1 million PSC records submitted to CH for such companies. Each PSC record captures a single relationship of ownership or control between a person of significant control and a registered company. PSCs can be individuals, but also companies or legal persons.

84. PSC records are not available for all registered companies. Some exclusions pertain to cases where there are security concerns about disclosing details about individuals, or where the company is exempt from CH reporting due to being listed on certain public exchanges. These make up a small portion of the full register: only around 300 companies (less than 0.01 percent of the total) fall under these exclusions. A more sizeable proportion of companies (approximately 300,000 records, around 6% of the total) do not have any PSC information, having submitted a statement to CH claiming that they have no PSCs or that the PSCs could not be found. It is possible for a company to have no PSCs according to the definition at paragraph 40 - for instance if there are more than 4 shareholders each holding less than 25% of shares

85. Our analysis focuses on PSC records where the controller is an individual (approximately 88% of the total) or a corporate entity (approximately 7%). We exclude a small proportion (0.1% of records) where the controller is a legal person.

86. Significant control over a company can be of multiple natures. The PSC records from CH differentiate between:

(a) Ownership of shares

(b) Voting rights

(c) Ability to appoint and remove directors

(d) Ability to appoint and remove members

(e) Ability to appoint and remove people

(f) Right to share assets

(g) Other significant influence or control

87. Each of these can be exercised directly as an individual, or indirectly via a trust or a firm. [65] For the ownership of shares, voting rights, and right to share assets, the level of control PSCs exert is recorded in three bands: 25 to 50%, 50 to 75%, and 75 to 100%. This, along with other features, affects how the PSC data can be used in an analysis of concentration and/or networks. We discuss this more below.

88. The CH data are not recorded in terms of the business hierarchy described in paragraphs 34(a) to 34(c). This is because ONS – the agency that maintains the IDBR – is required to maintain the IDBR in accordance with the European Union's regulation on the harmonisation of business registers for statistical purposes (EC No 177/2008). CH is not subject to the same requirement. However, because they both contain similar information, and the IDBR is in part derived from CH data, there is correspondence between the two. Companies as they are recorded in the CH register can be best thought of as either local units or enterprises.

Identifying PSCs and estimating ownership groups

89. The data available from CH do not contain unique identifiers for individuals or corporate entities that are recorded as PSCs. As a result, it is not straightforward to understand from the data whether one individual or entity holds control in multiple companies.

90. As an example, consider an individual, Frank Smith, who is recorded as a PSC for two different registered companies, A and B. Both of these relationships would be recorded in the CH PSC data. However, there is no common identifier across the two records that tells us they refer to the same "Frank Smith". This is consequential for our intended use, as it would prevent us from knowing that companies A and B have a common controller.

91. To address this issue, we carried out a probabilistic record linkage exercise following the theoretical approach in Fellegi and Sunter (1969).[66] The aim of this exercise is to estimate the probability that any given pair of PSC records represents the same entity (be it an individual or a company). The process works in the following way:

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[65] Slightly different definitions apply to Limited Liability Partnerships. See the PSC guidance (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/753028/170623_NON-STAT_Guidance_for_PSCs_4MLD.pdf) for more details.

[66] Fellegi, Ivan P., and Alan B. Sunter. 1969. "A Theory of Record Linkage." Journal of the American Statistical Association 64: 1183–210.

92. For each pair of records, a set of data fields is compared. For example, we might compare the "first name", "surname", and "date of birth" fields in Table B.1 below.

93. Each field is assigned a discrete 'similarity score' based on how similar it is across the two records (denoted by 'Simil.' in Table B.2). In Table B.1 for example, for the pair r1-r2, the first name and date of birth are exactly matching while the surname matches to a high degree. For the pair r2-r3, all fields have low similarity scores. The similarity scores are shown in Table B.2.

94. The distribution of the similarity score across all records is then used to compute a match weight for the corresponding field, which estimates the ability to discriminate between matches and non-matches across records. In cases like the one shown in Table B.2, the first name field will be less informative than the date of birth: intuitively, two records sharing first name is less of an indication that they might be referring to the same individual than two records sharing date of birth, especially when some first names are very common.

95. Finally, the weights for all the fields are combined into a single match probability.[67] The pair r1-r2 in Table B.2 is assigned a high match probability, as most of the fields match closely.

Table B.1: Example of individual PSC records to be linked

ID	First name	Surname	Date of birth
r1	Frank	Smith	01/03/1970
r2	Frank	Smyth	01/03/1970
r3	Carol	Lions	23/08/1984
r4	Anne	White	23/08/1984
...	...	...	...

Source: fictional example of PSC records created by the CMA

[67] We used the implementation of the Fellegi-Sunter approach contained in Splink, an open source software project developed by the UK Ministry of Justice. See the project's GitHub page (https://github.com/moj-analytical-services/splink) for more details.

Table B.2: Comparison table of individual records and their similarity scores

	First name			Surname			Date of Birth			Match prob.
	Left	Right	Simil.	Left	Right	Simil.	Left	Right	Simil.	
r1-r2	Frank	Frank	Exact	Smith	Smyth	High	01/03/1970	01/03/1970	Exact	.95
r1-r3	Frank	Carol	Low	Smith	Lions	Low	01/03/1970	23/08/1984	Low	0.05
r1-r4	Frank	Anne	Low	Smith	White	Low	01/03/1970	23/08/1984	Low	0.05
r2-r3	Frank	Carol	Low	Smyth	Lions	Low	01/03/1970	23/08/1984	Low	0.05
r2-r4	Frank	Anne	Low	Smyth	White	Low	01/03/1970	23/08/1984	Low	0.05
r3-r4	Carol	Anne	Low	Lions	White	Low	23/08/1984	23/08/1984	Exact	0.1
…										

Source: fictional example of PSC records created by the CMA. 'Simil.' Is short for similarity.

96. To compare individual PSC records, we used the following fields: forenames (all first and middle names), surname, date of birth (year and month only), title gender (whenever the record contained a gendered title like Mr, Ms, Lord, Dame, etc.), and the postcode of the service address. To limit the number of comparisons, we only considered pairs where either the date of birth and the forenames, or the date of birth and the surnames, were exactly matched – an approach called *blocking*. To compare corporate PSC records, we used the following fields: company name, registration number (a free text field that can contain for example a CH Company Reference Number (CRN)), and the postcode of the service address.

97. After having assigned a match probability to each pair of records in the PSC data, we consider records with match probability exceeding 85% to be referring to the same individual or company. In Table B.2, for example, that implies that records r1 and r2 are considered to be referring to the same individual. This threshold is arbitrary, but in our tests, it delivered a reasonable compromise between capturing common patterns (such as spelling mistakes, different use of middle names, acquisition of a spouse's surname, etc.) and excluding clear non-matches.

98. The pairs of linked records that we obtain in this way can be used to infer which PSC records refer to the same entity (individual or company). We assign a novel unique identifier to each entity. In Table B.1, for example, records r1 and r2 will be assigned the same individual identifier.

99. It must be highlighted that the process of probabilistic record matching is inherently imperfect: some false matches will exceed our chosen probability threshold, and some true matches will fall below it. However, we believe that this exercise allows us to more accurately map the network of relationships in the CH data, rather than simply considering exact matches across all relevant fields.

100. Having obtained uniquely identified controlling entities, we are able to estimate and allocate companies to “common ownership groups” – groups of companies that are linked through chains of significant ownership or control. The companies in these groups can be linked by control other than ownership, for example the ability to appoint and remove directors. However, we refer to them with the broad umbrella term “common ownership groups” because common ownership and its impact on competition is the focus of this chapter.

101. Specifically, we estimated common ownership groups in two ways, basing them on links between companies involving:

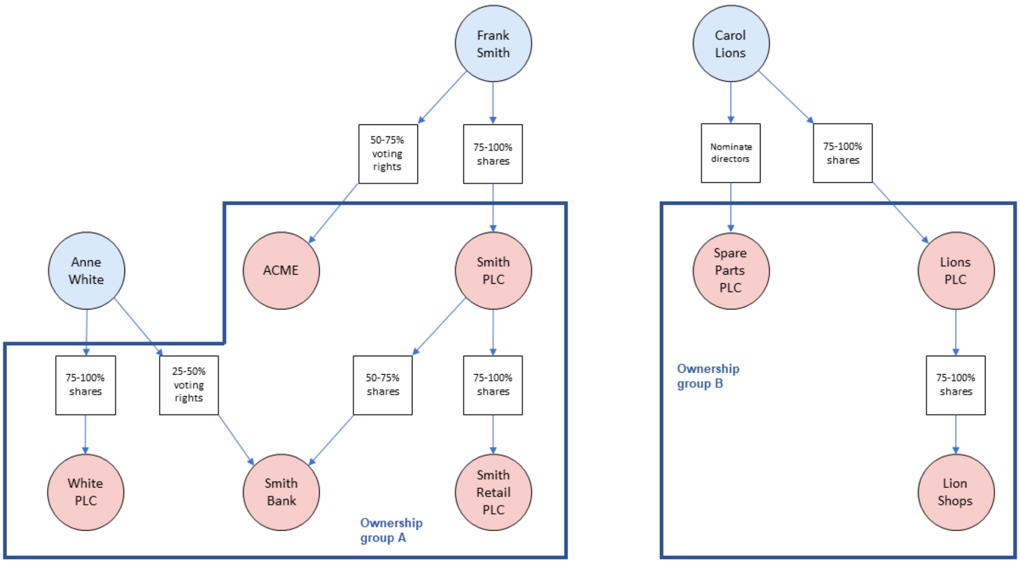
(a) more than 25% shareholdings, voting rights, or rights to share assets or the ability to nominate the majority of directors, people, or members of the company; and

(b) more than 50% shareholdings, voting rights, or rights to share assets or the ability to nominate the majority of directors, people, or members of the company

102. Consider the situation depicted in Figure B.2, with a network of eight hypothetical companies (in red) and three individuals (in blue) connected by various ownership or control relationships. In our approach, the eight companies would be allocated to just two distinct common ownership groups. Ownership group A (left-hand-side) would be made up of five businesses associated with two main PSC, Frank Smith and Anne White. If one of the companies was not in an ownership chain, we would treat it as its own entity.

103. Our methodology accounts for direct links between companies through common ownership. For example, it identifies where Spare Parts PLC and Lions PLC have a common owner. However, it also captures indirect links between businesses like White PLC and Smith Retail PLC by searching for connections that go beyond direct common ownership.

Figure B.2: Example illustration of ownership groups



104. As we discussed in the main body of the report, our definition of common ownership groups is sensitive to the threshold used for shareholding, voting rights, or rights to share assets. The CH data only contains information on these controls at over 25%, and in three bands: 25 to 50%, 50 to 75%, and 75 to 100%. It is for this reason we opted to present two sets of results based on the conditions in paragraph 59. Using 25% as the threshold for defining common ownership groups accounts for the smallest degree of control available in our data. Using 50% decreases the size of common ownership groups we find in the data. At the same time, and because of the structure of the CH data, control involving shareholdings, voting rights, or rights to share assets below the 25% threshold will not be captured in either case. We discuss how this affects our analysis of concentration below.

105. From this entire process we produce two datasets:

(a) a CH dataset of records of control augmented with unique identifiers for controlling individuals and companies; and

(b) A CH dataset of the entire register of UK companies augmented with a unique identifier for the ownership group we estimate they are a part of This is the primary dataset we use in our analysis.

Linking the CH data with the IDBR

106. Ideally, both the IDBR and CH data would record information at the same level of aggregation within a business. This would mean that any data in the

two datasets are directly comparable. However, the IDBR contains turnover and employment recorded at the enterprise level, whereas the CH data records information on companies. As we described in paragraph 46, roughly speaking, a company can be either an enterprise or a local unit in terms of the business hierarchy in Figure B.1.

107. As a result, a single enterprise in the IDBR can be associated with multiple companies in the CH data. The IDBR also contains a list of all the companies associated with each enterprise, meaning we were able to match companies from our new datasets to the IDBR based on their unique CRNs.

108. Our analysis focussed on linking the dataset 6363(a) , the entire CH register augmented with common ownership groups, to the IDBR. Roughly 79% of IDBR enterprises were matched to at least one company in this data.[68]

109. There are three main reasons why we might not be able to match companies across the two records:

(a) Companies in the CH data might not be captured by the IDBR because it does not cover businesses that are not PAYE or VAT registered.

(b) There might be inconsistent recording of company numbers across the two datasets that leads to matches not being found when in fact they should.

(c) Our snapshot of the CH records dates from roughly two months *after* the snapshot of the IDBR. It might be that the CH data contains some newly registered companies not included in the IDBR as a result.

110. CRNs are maintained rigorously across both the IDBR and CH data, so we deem that (b) is unlikely. In addition, we cannot know the extent to which (c), the registration or closure of companies, affects the match rate. Data on the rate of monthly (or quarterly) business formation and dissolution suggest this would not account for a sizeable portion of the difference, however. [69] As a result, although we cannot be certain, we deem that (a), the difference in the coverage of the two datasets drives the mismatch.

111. It is likely that a large portion of the roughly 21% of IDBR enterprises that could not be matched to a company in the CH records are those that are included in the former but not the latter. In particular, sole proprietors are not

[68] The rate is marginally lower when linking the IDBR tor the CH data on records of control. This is to be expected given the coverage of the data relative to the database on all companies and their ownership groups.
[69] See, for example, the rate of business creation since the beginning of the coronavirus (COVID-19) pandemic: https://uk-covid19-firm-creation.netlify.app/data/.

required to submit their company documents to CH, but will be included in the IDBR if they are VAT or PAYE registered. It is estimated that this type of company comprises around 56% of all businesses in the UK.[70]

112. In the other direction. roughly 57% of CH companies (and records) in the CH register data on records of control (74(a)) were successfully linked to an enterprise in the IDBR.[71] Again, we rule out paragraphs 67(b) and 67(c) as having a significant effect on the match rate, deeming 67(a) as the main determinant.

113. The ultimate goal of our analysis is to examine common ownership and adjusted concentration across UK SIC sectors. In particular, our aim is to tie this analysis as closely as possible to our main concentration analysis in Chapter 2 and Appendix A. Doing so would facilitate a discussion of our results in terms of our analysis of standard measures of concentration.

114. As such, in our final datasets we keep all enterprises in the IDBR and the details of the companies and PSCs they are associated with. We exclude all companies from the CH data that were not successfully matched to the IDBR. We make this exclusion because we cannot attribute these companies to an IDBR enterprise, and thus lack comparable information about turnover.[72] Again, we believe the primary reason for non-matches across the two datasets is a difference in their coverage. This means our merged IDBR CH data does not, in theory, include PSC information on:

(a) Sole proprietorships. However, these businesses do not have directors or shareholders meaning they would not have any PSC over and above the proprietor. Although this proprietor might be a PSC in other companies, these businesses tend to be relatively small - only 13% of the roughly 3.2 million are registered to pay VAT (which requires a turnover of greater than £85,000) or PAYE.[73]

(b) Businesses that are not VAT or PAYE registered. Because these types of businesses are likely to be very small, it is unlikely their inclusion would significantly alter any findings as they pertain to the level of concentration in UK industries.

70 Business population estimates for the UK and regions 2021: statistical release.

71 Again, the match rate was lower when considering matching companies' PSC records to the IDBR because some companies do not have any PSC records (roughly 6%, see paragraph 42).

72 The CH data do contain information on primary industry and could be linked to other sources of financial information at the company level. However, we link to the IDBR for the reasons described in this paragraph.

73 Business population estimates for the UK and regions 2021: statistical release

115. Overall, it is estimated that the IDBR – which serves as our primary data frame – covers around 98% of economic activity in the UK. As a result, we do not see these differences in coverage as a major limitation of our new data source.[74]

116. From the linking process described in this section, we again produce two datasets:

(a) an IDBR dataset augmented with unique identifiers of the companies and PSC businesses are associated with; and

(b) an IDBR dataset augmented with unique identifiers of the companies and common ownership groups businesses are associated with.

How we count businesses and calculate or measures of adjusted concentration

117. In the results section of Chapter 3 we discuss the reduction in the number of independent businesses in our data that occurs after we account for common ownership groups. There are two ways to count/define this number.

118. First, we can count the number of unique businesses across the whole economy. This would mean all businesses in a common ownership group, regardless of the sector they operate in, would be considered as one business. Counting this way suggests a reduction of 271,851 businesses from 2,589,993 to 2,318,142.

119. However, main concentration analysis in Chapter 2 defines businesses as IDBR enterprises that are in the same enterprise group *and* operate in the same 4-digit SIC industry (for consistency, we exclude the same non-market, government dominated, and heavily regulated industries noted in Annex A, paragraph 26). Therefore, a second way to count the number of effective business after considering ownership groups is to combine business within an ownership group that are part of the same industry. Counting this way, we find a drop of 93,489, from 2,646,384 businesses to 2,552,895. Although the number of businesses identified is higher in this case, the difference here is smaller because we break links that stretch across different 4-digit SIC industries.

120. The number of businesses that are part of a common ownership group with at least one other business can also be counted in these two ways. When discussing our results in Chapter 3, we reference the fact that we find 157,350

74 The Business Structures Database User Guide provides more information on the IDBR.

(although it is rounded to 160,000 in the text) such businesses. This is based on the second method of counting. Using the first, and accounting for cross-industry links, we find that 451,397 are part of a common ownership group

121. Both our standard and adjusted measures of concentration use the second rule for defining a business and calculating market shares. That is, to calculate market shares, we define businesses as:

(a) enterprises part of the same enterprise group and operating in the same industry in our standard method; and

(b) enterprises part of the same common ownership group operating in the same industry in our adjusted method.

122. In both cases we combine the turnover of all the enterprises within these 'businesses'. As a result, we do not account for cross-industry links among businesses in the same ownership group.

123. Further, because businesses in the IDBR can be linked to more than one company in the CH data, they can also be linked to more than one common ownership group. This occurs for 5,862, or 0.2%, of enterprise groups in the IDBR – a very small proportion. In these cases:

(a) Where an enterprise was linked to more than two common ownership groups, we chose the most frequent common ownership group.

(b) When there were ties, or a business was only linked to two common ownership groups, we selected one at random.

124. Although these links might be informative of common ownership, we make this choice to assign the turnover of an enterprise to one common ownership group.

125. An alternative might be to assign the turnover of such enterprises to each ownership group with which they are associated. This would mean double counting the enterprise in industry level calculations of the C10 and HHI. Another option might be to join the multiple common ownership groups with which an enterprise is associated into one entity. We do not opt for this approach to avoid grouping many businesses together into one entity that might only be joined by a very loose link.

126. The fact there is not always a one-to-one match between CH companies and IDBR enterprises also creates a challenge in assessing the ownership of PSC and ownership groups in an overall enterprise. As we discussed in paragraph 46, companies in the CH register can be either local units or enterprises. We

do not have information on turnover or employment at the local unit level, however. As a result, it is not straightforward to understand how ownership in a local unit translates to ownership in an enterprise. As such, where an enterprise is matched to more than one company in our analysis, we treat all equivalent ownership/controls (for example 25% shareholdings in two separate local units) as equal

127. It is important that the limitations of the data outlined throughout this Appendix are considered when interpreting the results of our analysis of common ownership and adjusted concentration.

Differences in the effect of common ownership groups on the C10 and HHI

128. In our main results in Chapter 3, there are large differences in the impact of common ownership groupings on the C10 and HHI - across almost all sectors, the HHI is affected to a much greater extent. This is because the HHI is significantly affected by the grouping together of already large businesses.

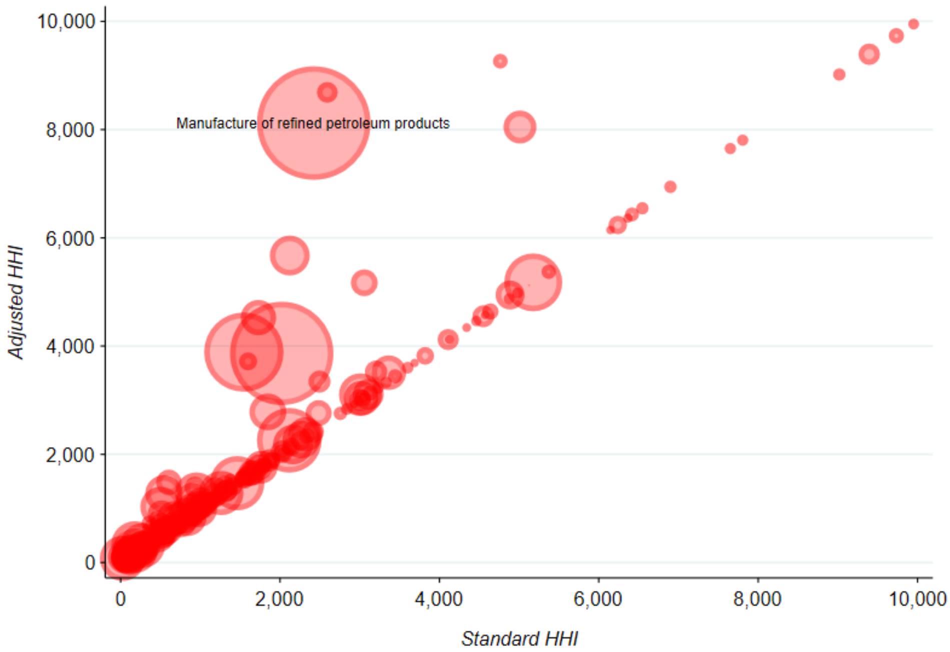
129. The manufacturing industry highlights this point well. It has a small increase in C10 of 3 percentage points, but its HHI Increases from 1,617 to 2,802. To show why this occurs, Figure B.3 shows the standard and adjusted HHI in all the underlying 4-digit SIC industries, with bubble size indicating their share of sector turnover.

130. There are five 4-digit industries whose HHI at least doubles (for some it triples) and have a relatively large share of industry turnover. The 4-digit industry 'Manufacture of refined petroleum products', is indicated by the larger bubble in the top left of the graph. Its HHI increases from 2,423 to 8,121, but its C10 from 98.3% to 99.4%.

131. This industry has a few large and many smaller businesses, meaning its C10 is already high. This relatively high C10 is accounted for in the standard measure of concentration. Grouping businesses into ownership groups brings together the largest businesses in this industry, however, tripling the market share of the largest effective business. On the other hand, mechanically, the businesses this grouping pulls in to the top 10 in the industry only have very small market shares. As a result, the C10 only increases marginally.

132. Calculating the adjusted HHI, however, now involves squaring a market share that is at least three-times as large as that of the largest business when using the standard method. Finally, because this industry has a large share of sector turnover, it weights heavily in the aggregated sector level HHI, pulling the average up substantially.

Figure B.3: standard and adjusted HHI in the 4-digit manufacturing industries, bubble size indicating industries' share of sector turnover



Source: CMA analysis of CH and IDBR data.

133. Because it is large businesses that are grouped together, these changes occur even without large differences in the number of effective businesses within the industries. Table B.3 below shows the difference in HHI alongside the change in the effective number of businesses in the 4-digit manufacturing industries that experienced the five largest changes in HHI. Industry codes are included here due to the long names of these industries. It shows the large changes in HHI are not necessarily accompanied by proportionately as large changes in the effective number of businesses within the industries.

Table B.3: the difference in HHI and number of businesses in the 4-digit manufacturing industries with the five largest changes in HHI, using only a 25% filter for common ownership groups

4-digit SIC industry code	Share of sector turnover (%)	Standard HHI	Change 25% filter	IDBR businesses	Change 25% filter
1012	0.87	1,729	2,799	93	-7
1101	1.17	2,122	3,552	879	-38

1920	12.14	2,423	5,699	90	-12
2332	0.21	2,593	6,096	141	-10
3030	5.61	1,546	2,344	612	-21

Source: CMA analysis of CH and IDBR data.

134. Importantly, as we suggested in the main chapter, there are in fact two extremely large common ownership groups that account for much of the adjustment we see to both the C10 and HHI. These common ownership groups stretch across multiple sectors and are derived from the wide networks of some of the largest businesses in the IDBR.

135. For example, there is one common ownership group comprised of roughly 17,000 businesses that span over nearly all SIC sectors. The businesses that are grouped together in the 4-digit industry 'Manufacture of refined petroleum products' (shown in Figure B.3, 1920 in Table B.3) are actually part of this ownership group.

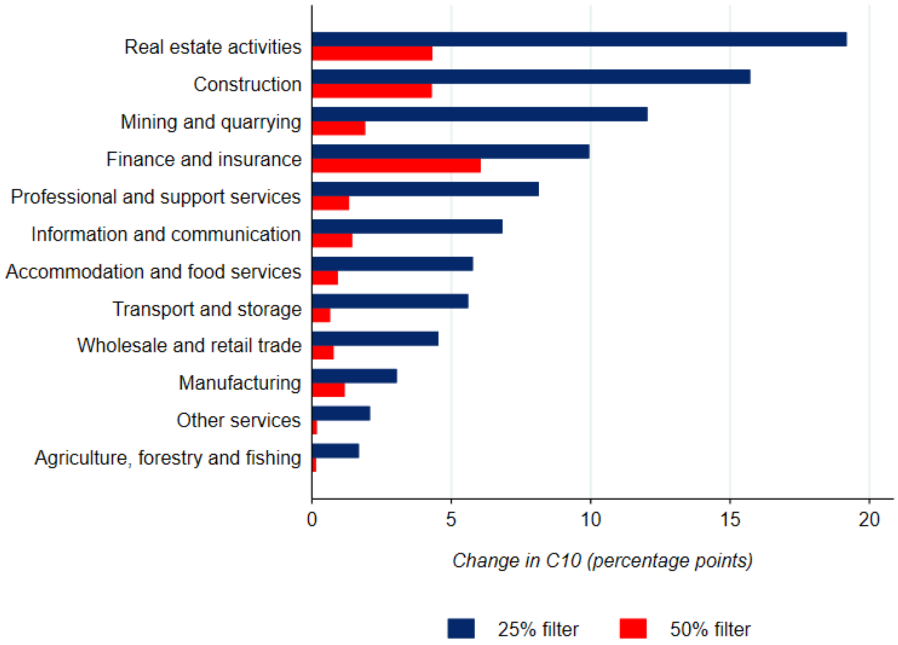
136. We pick up on the very wide networks because so far in this Appendix – and in Chapter 3 of the report - we have defined common ownership groups based on the minimum level of control measured in our data. However, the number of businesses in this (and other large and small) common ownership group decreases when we increase the threshold for ownership/control at which we group businesses together to 50%.

The effect of increasing the threshold for defining common ownership groups

137. Figure B.4 and Figure B.5 below show how the adjustments to the C10 and HHI compare when we define common ownership groups using 25% and 50% ownership of shares, voting rights, or rights to share assets as the thresholds. In both of these cases we maintained he ability to nominate directors, members, or people as criterion defining groups. We show the change in the two metrics in the graphs for a direct comparison of the magnitude of the adjustment that occurs.

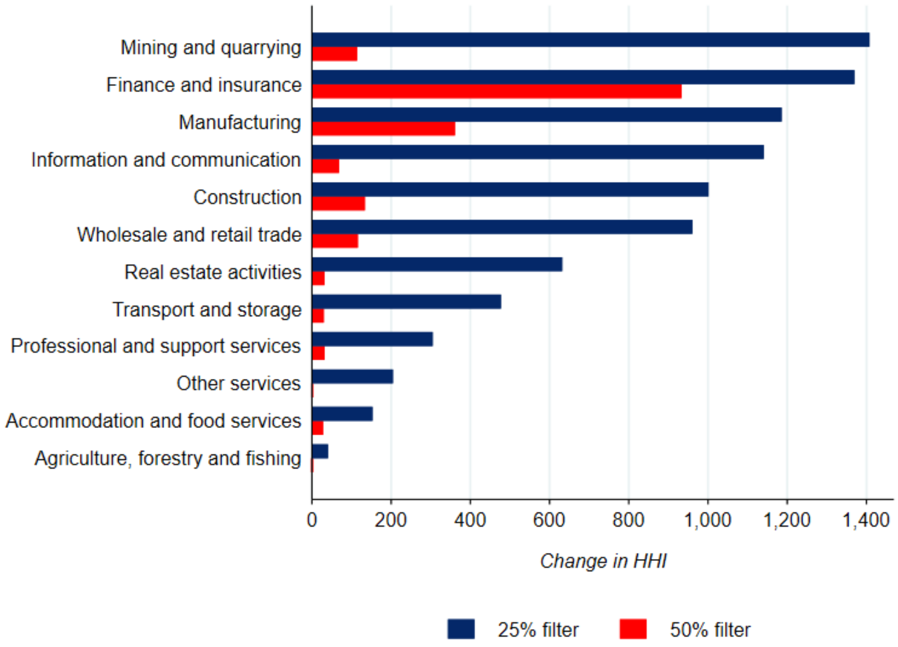
138. Across both the C10 and HHI the adjustments are considerably smaller for most sectors. This happens for the reason we have discussed throughout the main report and this Appendix: we estimate smaller common ownership groups when we increase the thresholds that define them.

Figure B.4: the adjustment to the C10 across UK SIC sectors when using no filter and a 50% filter to define common ownership groups, ordered by standard C10 from highest (left) to lowest (right)



Source: CMA analysis of CH and IDBR data.
Note: C10s are calculated for 4-digit SIC industries, and then averaged at sector level using industries' share of sector turnover as weights. The bars represent the difference in these averages when they are calculated using IDBR businesses versus common ownership groups. Professional and support services includes both Professional, scientific and technical activities, and Administrative and support service activities. Other service activities includes Arts, entertainment and recreation, and Other service activities (including the repair of goods, and personal services). Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example 'Activities of religious/political/trade union organisations', and 'Activities of households as employers of domestic personnel'. The 4-digit industry 'Wholesale of solid; liquid and gaseous fuels and related products' and several as its turnover disproportionate affects our results.

Figure B.5: the adjustments to the HHI across UK SIC sectors when using a no filter and a 50% filter to define common ownership groups, ordered by standard C10 from highest (left) to lowest (right)



Source: CMA analysis of CH and IDBR data.
Note: HHIs are calculated for 4-digit SIC industries, and then averaged at sector level using industries' share of sector turnover as weights. The bars represent the difference in these averages when they are calculated using IDBR businesses versus common ownership groups. Professional and support services includes both Professional, scientific and technical activities, and Administrative and support service activities. Other service activities includes Arts, entertainment and recreation, and Other service activities (including the repair of goods, and personal services). Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example 'Activities of religious/political/trade union organisations', and 'Activities of households as employers of domestic personnel'. The 4-digit industry 'Wholesale of solid; liquid and gaseous fuels and related products' and several as its turnover disproportionate affects our results.

139. Table B.4 shows this explicitly by replicating Table B.3 above, now including the change to HHI and number of effective businesses when the 50% filter is applied. In all but one of the industries there is a considerably smaller reduction in the number of effective businesses. For the Manufacture of refined petroleum products industry (1920), which has served as an example to this point, increasing the filter in fact breaks up the PSC group that drove its large increase in HHI before increasing the filter threshold

140. We could also alter the filter in some other way, for example choosing a 75% threshold or 25% for shareholdings and 50% for voting rights. This would result in different estimates of common ownership groups and adjustments to the C10 and HHI. We leave this refinement for future research.

Table B.4: the difference in HHI and number of businesses in the 4-digit manufacturing industries with the five largest changes in HHI, using both 25% and 50% filters for common ownership groups

4-digit SIC industry code	Share of sector turnover (%)	Standard HHI	Change 25% filter	Change 50% filter	IDBR businesses	Change 25% filter	Change 50% filter
1012	0.87	1,729	2,799	579	93	-7	-3
1101	1.17	2,122	3,552	1	879	-38	-7
1920	12.14	2,423	5,699	1,341	90	-12	-3
2332	0.21	2,593	6,096	6,096	141	-10	-10
3030	5.61	1,546	2,344	243	612	-21	-14
Total	4.00	2,082	4,098	1,652	363	-18	-7

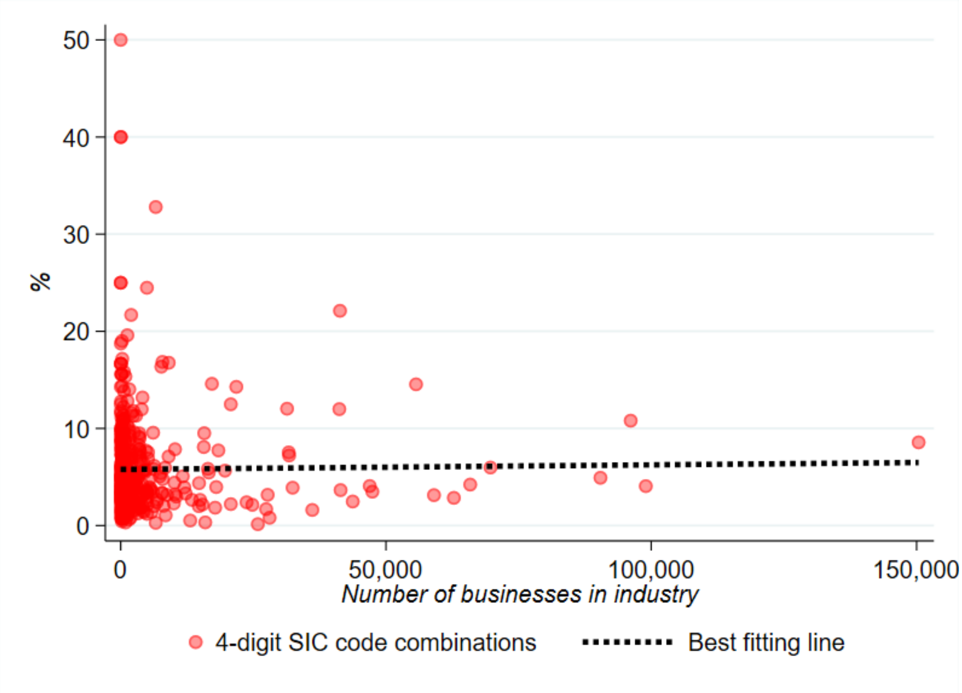
Source: CMA analysis of CH and IDBR data.

The prevalence of common ownership and industry size

141. In the Chapter 3, we presented a descriptive statistic on the proportion of common ownership groups in each sector that were comprised of multiple IDBR businesses. We also noted there that this measure of the prevalence of common ownership is not related to industry size in terms of the number of businesses.

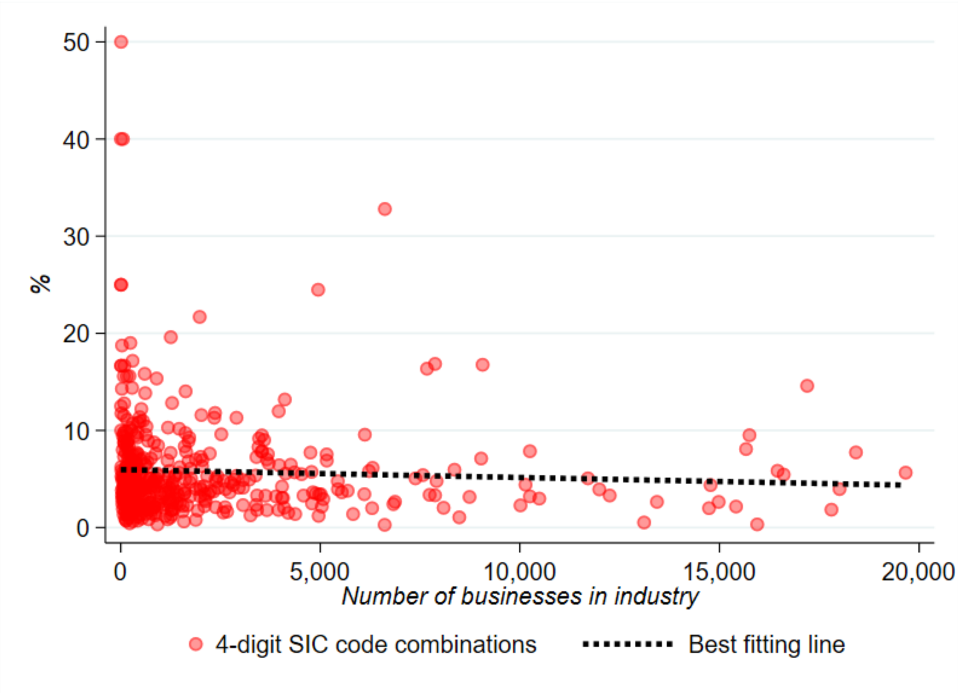
142. To show this, Figure B.6 below plots it against the number of firms in 4-digit SIC industries, overlaying a best-fitting line that aims to show if the two are related linearly. This does not appear to be the case. However, there are a few large, outlying industries in terms of the number of businesses that dominate the scale of the plot. Figure B.7 therefore presents an identical comparison but focusing only on industries with fewer than 20,000 businesses (an arbitrary cut-off that does not affect the conclusions we draw).

Figure B.6: the proportion of PSCs with ownership or control in multiple businesses versus the number of firms, across all 4-digit SIC industries



Source: CMA analysis of CH and IDBR data.

Figure B.7: the proportion of PSCs with ownership or control in multiple businesses versus the number of firms, across 4-digit SIC industries with fewer than 20,000 firms



Source: CMA analysis of CH and IDBR data.

International Trade and Competition

143. In recent years, there have been growing concerns that concentration within markets is on the rise.

(a) Within the U.S. several papers have suggested that concentration in the U.S. has changed due to a shift towards less competition and higher market power among firms (see for example Covarrubias, Gutiérrez and Philippon (2020), Gutiérrez and Philippon (2017), De Loecker, Eeckhout and Unger (2020)) and Grullon, Larkin and Michaely (2019)).

(b) However, some have argued that the documented rise in concentration is in fact due to the rise of more efficient "Superstar Firms" and is therefore not a reflection of weakening competition but greater efficiency as markets shift towards a 'winner-takes-most' environment (Autor et al 2020).

(c) Interestingly, there is some evidence that the U.S. may be diverging from Europe in terms of which trend is dominant. Philippon (2019) argues the U.S. is no longer the home of free markets and that Europe has supplanted it as a beacon of what healthy competition looks like.

(d) Bighelli et al (2020) also argues that the increasing market concentration in Europe is not a cause for concern, and instead reflects the growth of more efficient firms.

144. However, all the above studies rely on measures of 'Producer Concentration' and have little, if any, accounting for importers and the role of exports. When discussing the effective level of concentration within a market, we must consider foreign firms and foreign sales in order to understand what exactly domestic consumers face.

Seller vs Producer Concentration[75]

145. The literature on how international trade affects domestic markets is vast but few papers consider what we define as *Seller Concentration*, i.e., the pool of firms that consumers within a given country engage with. Many instead focus on *Producer Concentration*, i.e., they study firms who produce within a country and pay less attention to both where that output is sent and what

[75] Concentration is merely one indicator of the state of competition in a market. High levels of concentration may indicate uncompetitive conditions or be a result of large efficient firms.

comparable imports may exist in the same market. See Carr & Davies (*forthcoming*) for discussion of this issue.

146. Two interesting exceptions to this literature that do attempt to measure *Seller Concentration,* Amiti and Heise (2021) and Feenstra and Weinstein, 2017.

147. Amiti and Heise (2021) they refute concerns of rising concentration in the U.S. by detailing how previous studies only cover a domestic phenomenon, counteracted by the growth of foreign firms, mostly at the bottom of the sales distribution. Their work represents one of the first studies to use data on the universe of firms, both foreign and domestic to measure concentration.

148. Feenstra and Weinstein (2017) estimate the average US market share for importing firms based on their country's total share of exports into the US market, and an indicator of the level of concentration within that origin country. This variable is then used to derive an estimate of markups. Their study suggests that between 1992 and 2005 US import shares rose and US firms exited, leading to an implied fall in markups, while the total number of varieties being sold in the market increased because of imports.

Two & A Half Theories of Trade

149. The study of international trade is dominated by two paradigms, the theory of comparative advantage based on perfect competition, and the theory of product differentiation and increasing returns based on monopolistic competition. By comparison analysis of the role of large firms in international trade has not had as much attention (Neary, 2010).

   (a) The traditional comparative advantage based models of trade emerge either from differences in labour productivity due to technology (the Ricardian model) or from differences in natural resources (the Heckscher-Ohlin Model). The key prediction of this first paradigm is countries will produce and export those goods that they can make at a relatively (compared with other countries) lower opportunity cost (Ranjan and Raychaudhuri, 2016).

   (b) The characteristics of this second paradigm, are trade being driven by economies of scale rather than factor endowments or technology (Krugman 1979), the presence of product differentiation which gives rise

to monopolistic competition (Krugman 1980), and heterogenous firms (Meltiz, 2003).[76]

(c) Both Neary (2010) as well as Head & Spencer (2017) track and discuss the waxing and waning interest in this third paradigm, and discuss the reasons why oligopoly in international trade has not received as much attention but may be making a comeback.

150. For the purposes of this paper two of the most relevant works in this resurgence are that of Shimomura & Thisse (2012) and Parenti (2018).

(a) Shimomura & Thisse (2012) model a hybrid market combining elements of oligopoly and monopolistic competition. They characterise a domestic market with an exogenous number of large firms and a monopolistically competitive fringe determined by free entry and exit. In this model when faced with entry by a large (foreign) firm, the fringe shrinks, competition increases, and welfare improves.

(b) Parenti (2018) expands on this hybrid approach by allowing the large firms to decide how many products to offer. Trade liberalisation can then increase or decrease welfare depending on trade costs, and the number of trading partners / large foreign firms.

151. Finally, we would be remiss to not mention a paper by Cowling et al (2000) which pointed out the issue we are attempting to solve over 20 years ago. For a sample of transportation industries within the UK they demonstrate how concentration has been incorrectly measured due to an assumption that all imports are competitive and thus a solely deconcentrating force.

Imports and Competition

152. A review of the literature on international trade and domestic market performance by De Loecker and Goldberg (2014) found "If there is one robust finding that the literature has delivered to date, it is that industry profitability increases with exposure to foreign competition." (p.222). The exact mechanism behind why this occurs is not always clear. As note in the review recent evidence would suggest that both price/markup effects as well as (physical) productivity improvements play a role. More research is needed in this area to clarify how these two effects vary between industries, countries and different goods and services.

[76] See also Norman, 1976; Lancaster, 1980; Helpman 1981; Helpman & Krugman 1987 and Dixit & Norman, 1980.

(a) As early as 1971 (Esposito and Esposito) researchers have used the ratio of imports to domestic sales as an explanatory variable in analysis. The authors of this early paper found that an increase in import penetration exerts a significant negative pressure on domestic firms' profits.

(b) Pavcnik (2002), found trade liberalisation enhances plant productivity. The main channel being a reallocation toward more efficient firms which accounted for two-thirds of the productivity growth at the industry level, while within-firm learning accounted for the remaining one-third.

(c) Syverson, 2011 details several papers linking the presence – or even just the threat – of imports with improvements in productivity domestically, but notes "The specific mechanisms through which trade-oriented competition can increase productivity do vary across the papers, from quality upgrading within plants to heightened selection across plants." (p.353).

153. With that said, there is a clear issue in not modelling the importer side of these events. Importers can place pressure on domestic firms but be inefficient or abusive themselves. As a simplified example, imagine a foreign giant that enters the domestic market via predatory pricing to establish a position of dominance.

(d) Edmond, Midrigan and Xu, 2015 note that trade can be pro-competitive and bolster productivity but in order for this to happen 2 conditions must be met. First, the market in question must already contain extensive misallocation (i.e., the most dominant firms are charging high markups). And second, when trade occurs it must bring about *head-to-head competition*. If one country is substantially more productivity than the other, trade can bring about negative outcomes be exacerbating the existing misallocation.

(e) Perhaps more tellingly, in the aptly named "The Elusive Pro-Competitive Effects of Trade" Arkolakis et al., (2019) find domestic and foreign markups are likely to respond very differently to trade liberalization, even going so far as to note that it is "perfectly possible for domestic and foreign markups to move in opposite directions" (p.77). This can occur if foreign firms absorb enough of the reduction in cost to offset any increase in competition.

Exports and Competition

154. It is not possible to correctly evaluate competition in a market without correctly accounting for exports. In terms of concentration, if we do not exclude exports

we will overstate the market shares of domestic producers in the domestic market, e.g., British firms will appear to have a larger share of total U.K. sales because we are not excluding their output that is sold overseas. This is particularly important given the following two results.

155. Exports are highly concentrated.

(f) Freund and Pierola, (2015) examine “Export Superstars” and find that in many cases a single firm can shape the export patterns of an entire country. They find the single largest exporter in a given country produced around 14 percent of that country’s total (non-oil) exports. With the top 5 biggest domestic firms produce 30% of that country’s total (non-oil) exports.

(g) Mayer and Ottaviano, 2008 also find the distribution of exporting activity is highly skewed towards the largest European firms.

156. Exporters are unique.

(h) Bernard et al., (2007) present several stylised facts about exporters. Exporting is relatively rare, in the US for example only 4% of firms exporting. Exporters are significantly larger and more productive. And they also pay higher wages (by 6%). Meanwhile Bernard, Jensen and Schott, (2009) note the “most globally engaged” firms are more likely to trade with difficult markets and perform foreign direct investment.

(i) Bernard et al., (2018) highlight that the role of “Global Firms” is still overlooked. They suggest existing firm level differences are magnified by participation in trade, and that global firms are of sufficient size to exhibit strategic market power in foreign countries as well as their own.

Imported Intermediates and Competition

157. Lowering tariffs on output can generate tougher import competition and stimulate an increase in productivity, but lowering input tariffs, which can generate learning, variety, and quality effects, can be twice as effective at improving the productivity of domestic firms.

158. Goldberg et al., (2010) find evidence in India that a massive increase in product scope in the 1990's was a result of a reduction in import tariffs making existing imported intermediates cheaper and making new imported intermediates available for the first time. The lowering of these trade tariffs acted as a relaxation of technological constraints faced by these Indian firms.

(j) Amiti and Konings (2007), Halpern, Koren and Szeidl (2015) and Kasahara and Rodrigue (2008) also provide evidence of a positive relationship between importing inputs and productivity.

159. The concentration seen in exporting is linked to imported inputs, with intermediate inputs accounting for a majority of international trade Johnson and Noguera, 2016.

(a) Bernard et al., (2018) also find that a substantial fraction of the firms that export, or import, do both. The largest and most productive firms are those most heavily integrated into importing and exporting activities.

160. Imported Inputs have many benefits outside of greater efficiency and variety.

(a) Amiti, Itskhoki and Konings (2014) show that exporting firms who also import inputs can insulate themselves from exchange-rate shocks and limit pass-through to consumer prices. This fact, combined with the fact the largest exporters are also the largest imports, can explain why large movements in exchange rates have little effect on the prices of internationally traded goods.

(b) De Loecker et al., (2016) find that even when trade liberalisation encourages direct competition prices may fall less than expected if firms are able to use cheaper imported inputs. The fall in marginal cost may even be greater than the fall in price meaning markups increase.

Appendix C: CMA analysis of UK markups and profitability

0. Measures of both markups and profitability have been used in the economics literature as indicators of the state of competition at the global level, or at the level of a country's economy. As set out in Chapter 4, the CMA has therefore considered trends in both markups and profitability (based on Earnings before Interest and Taxes (EBIT) margins and Return on Capital Employed (ROCE)) across the UK economy.

1. In this Appendix we set out the methodology and data that we have used to assess markups and profitability across the UK economy. While a firm's EBIT margin and ROCE are directly observable,[77] a firm's markup is not and has to be estimated.[78] Therefore, we also set out in detail the approach we have taken to estimating markups.

2. Finally, as set out in Chapter 4, it is important to compare trends in ROCE to trends in the cost of capital. In our analysis we have used a measure of the cost of debt as a proxy for the cost of capital, as explained in detail here from paragraph 53.

Measuring markups and profitability

3. In this section we first discuss the limitations inherent in using accounting data to estimate markups and profitability. We then discuss the available estimation methodologies for markups as well as specific limitations related to estimating markups and profitability respectively.

The use of accounting data

4. Accounting data has some strengths. Much of it is audited, which makes it reasonably reliable. Common accounting standards also mean that the data should be reasonably consistent across firms, making aggregation meaningful.

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[77] EBIT is reported by firms. We therefore use this variable and divide it by turnover to obtain the EBIT margin and divide it by capital employed to get ROCE.

[78] It is worth emphasising that given the level of aggregation considered, it is not possible to measure markups and consequently we rely on proxies or estimates, which are conditional on a variety of assumptions, as we will also discuss in the sections below.

5. However, there are drawbacks to using this data. Accounting data, and the metrics that can be estimated from it, do not map perfectly onto economically meaningful indicators. The drawbacks include the following.

(a) Accounting standards change over time. This means that the reported profits, or assets, of a firm may change as a result of changing accounting standards rather than because of any fundamental change such that any trends do not reflect changes in competition.[79]

(b) There are many companies registered in the UK whose business is largely or wholly overseas[80] (this includes exports and business that takes place purely outside the UK).[81] This means that measures of profitability and markups will be influenced by competitive conditions and other factors outside of the UK.

(c) Relatedly, profits may be booked in jurisdictions for tax purposes rather than reflecting underlying economic activity. This may lead to profits based on UK activity being under reported, although it is unclear how this would affect the trend over time.

6. As set out in Chapter 4, when the CMA assesses the profitability of individual firms in the context of a market investigation, it conducts a detailed analysis of the appropriate adjustments to make to the relevant accounting data (and uses confidential data in addition to the publicly available data we have used for this analysis).[82] However, it is not practical to do such detailed analysis as part of this report, or more generally in an assessment of competition across an entire economy.

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[79] For example, when an industry, or the economy as a whole, moves its accounting practices over time in a particular direction (eg to capitalise more intangible assets), trends in the aggregate metrics may result that are not explained by underlying developments in the industry, or in conditions of competition.

[80] While FTSE 350 companies are not representative of UK firms and are instead characterised by much greater levels of business outside the UK, the following statistics will serve to illustrate the point about overseas activity. Analysis by S&P Global in 2016 suggested that less than 43% of the combined revenues of the FTSE 350 index were associated with sales to Europe including the UK, while only 22% of revenues were specifically labelled as having been transacted in pound sterling (S&P Global (2016), Analyzing the Impact of Brexit Using Geographic Segment Data). To note, regional and currency reporting are not standardised across companies, so these figures represent only an estimate of the revenue exposure of the companies in the FTSE 350 index. For example, only 48% of the revenues analysed specified currency exposure. The regional data is potentially more robust, with S&P Global suggesting that 89% of the companies specified regional revenue exposures. As Europe including the UK will contain a substantial element of sales to European countries, it would seem to be reasonable to suggest that true UK exposure within this broad index of the 350 largest listed companies sits between 22-43%. While we are not able to quantify the proportion of foreign activity among the large companies that we analyse, it is worth noting that our choice of using unconsolidated accounts makes this problem much less severe, as much foreign activity finds its way into UK accounts precisely when the accounts of foreign entities are consolidated by a UK parent.

[81] For example, this might be where a UK-based mining company sells raw materials mined in country A into country B, neither of which are the UK.

[82] See also CMA (2017), Guidelines for market investigations: Their role, procedures, assessment and remedies (Revised).

7. Against this backdrop, we have focused our analysis on broad trends over time. We are not aware of any changes in reporting standards or practice that would bias this analysis of trends one way or another.

Estimation methodologies for markups

8. Firms' markups are not observed directly, as data on marginal costs is not readily available. Furthermore, when conducting an economy-wide analysis it is not practically possible to adopt the approach often taken in relation to specific firms or economic markets.[83]

9. Therefore, in order to derive marginal costs and estimate markups, the main approaches adopted in the literature are the following:

   (a) The demand approach starts from the assumption that firms set their prices to maximise profits given the demand curves they face for their products. This methodology requires information on prices and quantities at the product level for many firms and sectors over a long period of time, and an assumption regarding the applicable model of competition. For these reasons, it is difficult to apply this approach across very different sectors in an economy.

   (b) The production function approach, which was first developed in Hall (1988)[84] and advanced in De Loecker and Warzynski (2012),[85] starts from the assumption that firms decide which inputs to use to minimise costs, given the costs of these inputs and their production function. The markup can then be estimated using information on the cost of an input as a share of a firm's revenue (the 'input cost revenue share') and the extent to which the firm's output varies based on changes in the quantity of that input used (the 'output elasticity').

   (c) The cost share approach starts from the same premise as the production function approach (cost minimisation), but it uses a more straightforward methodology to estimate output elasticity, as we explain below.

10. The recent literature largely relies on the production function approach because it relaxes various restrictions of the demand methodologies while

[83] In the industrial organisation literature, marginal costs are usually derived by observing the prices charged by a firm, estimating the demand it faces, and solving the firm's profit maximisation problem. This approach, based on an in-depth study of a specific market, is clearly not suitable for estimating markups at the level of the whole economy.

[84] Hall, Robert E. (1988), The Relation between Price and Marginal Cost in U.S. Industry, Journal of Political Economy, 96 (5), p. 921–947.

[85] De Loecker, J. and Warzynski, F., (2012), Markups and Firm-Level Export Status, *The American Economic Review*, p. 2437-2471.

having strong theoretical underpinnings. However, it also presents some limitations:

(a) This approach requires data on input and output quantities, and this is not available in accounting data. Also, there is still no consensus on whether this methodology is practicable when the data relates to revenues and expenses.[86]

(b) While the methodology should in theory lead to the same results irrespective of the input used for the estimation, Diez et al. (2019) find that the choice of the input used for the estimation may have an impact on the estimated level and trend of markups.[87,88]

(c) The methodology is based on the assumption that firms have no market power in the markets in which they purchase inputs.[89] If this is not the case, then a firm's markup will be overestimated as it will capture a firm's market power in both the markets in which it purchases its inputs and the markets in which it sells its products.[90]

11. To facilitate the estimation of output elasticities, the cost share approach makes two additional assumptions: that firms have constant returns to scale (ie, that marginal costs do not vary with the quantities produced), and that the optimisation conditions hold for all inputs. including those that are costly to adjust like capital, at least on average across firms in a given sector. Under these two assumptions, the output elasticity of an input is equal to the share of the input in total expenditures. This approach has the benefit that it does not require data on output and input quantities – it can be implemented with data on expenditure, which is readily available in accounts.

12. We present a more detailed comparison of the production function approach and the cost share approach in the section below where we specify the methodology we adopted as well as the reasons underlying our choice.

[86] As we explain below, this is one of the main critiques raised by Bond et al. (2020). Steve Bond, Arshia Hashemi, Greg Kaplan and Piotr Zoch (2020), Some Unpleasant Markup Arithmetic: Production Function Elasticities and their Production Data, *NBER Working Paper No. w27002*.

[87] Moreover, Bond et al. (2020) show that, if an input is used to influence demand rather than to produce output – which is the case for advertising or other expenditure related to a firm's 'brand' – the markup would be underestimated.

[88] This might be due to the fact that the methodology is based on the use of a fully flexible input, that is, an input that adjusts with the level of production in the very short term. However, accounting data does not typically identify such inputs.

[89] That is, input markets are perfectly competitive. However, in principle, under some conditions this assumption can be relaxed.

[90] Syverson, C. (2019), Macroeconomics and Market Power: Context, Implications, and Open Questions, *Journal of Economic Perspectives*, pp23-43.

Measuring profitability

13. Our analysis has used a range of profitability measures, derived from accounting data, to assess the dynamics of competition at the economy level.[91] When assessing competition, however, we are interested in economic profits and these can differ in important respects from the profits contained in available accounting data.

14. The main metric of returns on capital that can be constructed using accounting data – the Return on Capital Employed (ROCE) – does not directly reflect economic profits without adjustments for (among others) the following two reasons.

15. First, it is not possible to adjust the accounting data for each firm to take into account expenditure that constitutes, from an economic perspective, capital investment, but which might not be recorded as such. For example, if a company hired an external educator to come in and train their staff, the cost of hiring this educator would likely to be recorded as capital investment; in contrast, if it the training was delivered from within the company, then it is likely that the cost of doing so would not be recorded as capital investment. This could make ROCE inaccurate as a true measure of return on capital. If the true amount of capital employed is higher than that recorded in company accounts, then the ROCE estimated on this basis will produce a misleadingly high estimate of profits.

16. Second, ROCE does not take account of the cost of the capital that is employed, nor does it make any allowance for past innovation or risk taking. If the cost of capital a firm faces rises exogenously, then, over time, it would be expected that ROCE would rise too as the hurdle rate for investment projects rises.

17. At the very least, these factors will affect the absolute levels of the profitability metrics we estimate. This means that it is difficult to comment on whether a certain measured absolute level of profit is 'too high'.

18. Normally, when the CMA assesses the profitability of individual firms in the context of a market investigation, it conducts a detailed analysis of the

[91] Some authors considering publicly traded firms have used firms' market value or dividends as a share of sales (see De Loecker, Eeckhout and Unger (2020) and Diez et al. (2018)). Aghion et al. (2005) constructed a price-cost margin measured by operating profits net of depreciation (Aghion, P., Bloom, N., Blundell, R., Griffith, R. and Howitt, P. (2005), Competition and Innovation: An Inverted-U Relationship, *The Quarterly Journal of Economics*, pp701-728). An estimated financial cost of capital, divided by sales and a similar metric is used by Gutiérrez and Philippon (2017) (Germán Gutiérrez and Thomas Philippon (2017), Declining Competition and Investment in the U.S., *NBER Working Paper 23583*). Furman and Orszag (2015) use ROIC (Return on Invested Capital), which is measured as net operating profit after tax divided by invested capital.

appropriate adjustments to make to the relevant accounting data (and uses confidential data in addition to the publicly available data we have used for this analysis).[92] However, it is not practical to do such detailed analysis as part of this report, or more generally in an assessment of competition across an entire economy.

19. Therefore, as with markups, trends (rather than the absolute level) in profitability metrics are likely to be more informative about the state of competition. However, results may still need to be treated with caution as the trend in accounting profits does not follow the trend in economic profits. For example, this would be the case if the proportion of true capital investment that is under recorded grows or shrinks over time.

20. Further, trends in profitability metrics based on accounting data at the industry sector or whole economy level may also be affected by various factors other than changes in the conditions of competition. These factors might include:

(a) changes in the capital intensity of an industry sector or the whole economy;

(b) changes in the level of intangible capital and human capital;

(c) changes in the overall opportunity cost of capital (which in turn will be affected by the balance between global savings and investment opportunities, as well as factors such as monetary policy, 'country risk', and regulations on the movement of capital); and

(d) where intangible capital is poorly recorded for accounting purposes, these will affect measures of returns on capital as well as measures of profit margins based on accounting data.

21. While these factors will have an impact on profitability metrics, we have not seen evidence that they are likely to impact strongly on overall trends. Analysing trends in accounting profits would therefore still provide useful information towards an assessment of the state of competition.

CMA approach in the estimation of markups

22. In this section we present the database used and the methodology adopted for the estimation of markups in the CMA analysis.

[92] See also CMA (2017), Guidelines for market investigations: Their role, procedures, assessment and remedies (Revised).

Data

23. Our analysis is based on the FAME database.[93] The database contains firm-level information on their financial statement submitted to Companies House in the UK. We have annual data for the period 2000 to 2020, which enables us to analyse the recent development of markups and profitability in the UK economy.

24. Our main variables of interest are turnover, cost of sales, EBIT and capital,[94] as well as industry classifications according to the UK Standard Industrial Classification of Economic Activities ("SIC classification").[95]

25. The data covers firms of 250 or more employees and includes listed and unlisted firms.[96] This is different from De Loecker, Eeckhout and Unger (2020) and Aquilante et al. (2019), who use data for listed firms only. Rather, our data is more comparable to Diez et al. (2019), who also have unlisted firms in their data (although they include firms with less than 250 employees in their data).

26. FAME includes data on both consolidated and unconsolidated companies accounts. We use only unconsolidated accounts because they offer better SIC classification. This is due to the fact that, for example, the parent's consolidated accounts might be registered as a 'holding company', not in the actual industry the group is active in. Also, large company groups can have subsidiaries active in different industries. Using consolidated accounts would mean losing this information. Finally, consolidated accounts may include turnover and profits of overseas subsidiaries whereas the focus of this report is, to the extent possible, turnover and profits made in the UK.

27. Finally, we decided to exclude certain SIC codes from the analysis. For example, we excluded 'Libraries, archives, museums and other cultural activities' and 'activities of sports clubs' because firms in these SIC codes are likely operate a different business model compared to the rest of the

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[93] The FAME (Forecasting Analysis and Modelling Environment) database is a time series database from SunGard.

[94] Turnover refers to the annual gross revenue companies earned in the UK – please note that the metric used in the CMA analysis does not include overseas turnover. The cost of sales are all costs directly associated with the creation of good and services sold and as such they do not include, for instance, indirect costs of sales such as marketing. EBIT is Earnings Before Interest and Tax and is reported by companies in their financial statements. Capital has been operationalised in our analysis as fixed assets in the main analysis and as total assets in the robustness check.

[95] UK Standard Industrial Classification of Economic Activities - SIC Code 2007.

[96] Specifically, our sample consists of around 4,000 UK companies having more than 250 employees.

economy. We also dropped observations for industry classifications codes where we have a small number of observations in our dataset.[97]

Methodology

28. In this section we present the methodologies we considered for the estimation of markups and the reasons underlying our choice.

29. As outlined in the section above, De Loecker and Warzynski (2012) proposed a production function approach to estimate markups.[98] This approach is based on the assumption that if firms minimise their costs then markups can be estimated using information on the cost of an input as a share of a firm's revenue (the 'input cost revenue share') and the extent to which the firm's output varies based on changes in the quantity of that input used (the 'output elasticity').[99]

30. More formally, the markup is composed of the output elasticity and the cost share in output:

$$\mu_{ijt} = \theta_{jt} \frac{P_{ijt}Q_{ijt}}{P_{ijt}^{V}V_{ijt}},$$

where θ_{jt} is the output elasticity of the input in industry j at time t, $P_{ijt}Q_{ijt}$ is the revenue of firm i operating in industry j at time t (P_{ijt} is the price and Q_{ijt} is the quantity of output sold), and $P_{ijt}^{V}V_{ijt}$ is the input cost of input V for firm i operating in industry j at time t (P_{ijt}^{V} is the price of the input V and V_{ijt} is the volume of input V).

31. To estimate the output elasticities, the academic literature has used different approaches. In subsections below we review two of them: the production function approach – developed in De Loecker and Warzynski (2012) and adopted also in De Loecker, Eeckhout and Unger (2020) – and the cost share approach.

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[97] We exclude the following list of 2-digit sic codes: 91 (Libraries; archives; museums and other cultural activities), 93 (Sports activities and amusement and recreation activities), 96 (Other personal service activities), 85 (Education), 37 (Sewerage), 36 (Water collection; treatment and supply), 12 (Manufacture of tobacco products) and 7 (Mining of metal ores).

[98] De Loecker, J. and Warzynski, F. (2012), Markups and Firm-Level Export Status, *The American Economic Review*, 102(6), pp2437-2471.

[99] The input must be a variable input, and this is referred to as the elasticity of output to a variable input which is measured as the percentage change in output resulting from a change in the quantity of input used. In addition, De Loecker, Eeckhout and Unger (2020) mention that the methodology can be adopted using any variable input and should in theory lead to the same markup estimate irrespective of the input used.

The production function approach

32. De Loecker, Eeckhout and Unger (2020) adopt the production function approach developed in De Loecker and Warzynski (2012) to estimate output elasticities. A fundamental problem when estimating production functions is that a firm's productivity, which is only observed by the firm but not by the analyst, determines the quantity of inputs it uses in production. For example, a firm with high productivity may decide to use less labour or intermediate inputs. This would introduce a bias when learning about the general proportion of inputs used in production.[100]

33. The literature has addressed this by using a two-stage instrumental variable approach[101] and De Loecker, Eeckhout and Unger (2020) build on those approaches when estimating output elasticities. A point of departure from existing work is that De Loecker, Eeckhout and Unger (2020) do not observe outputs but use revenue instead in their estimation of the elasticities. In fact, frequently the output of a firm is not directly observed, but revenue is observed.

34. Recently, Bond et al. (2020) provided a critique of the approach used by De Loecker, Eeckhout and Unger (2020). They highlight three points related to the use of the output elasticity, the identification of the output elasticity and the estimation of the output elasticity.[102] First, Bond et al. (2020) argue that it is important to use the output elasticity, not the revenue elasticity. Second, they argue that if the input faces adjustment costs (eg labour market frictions) or the input is used to shift demand (eg through advertising), the markup cannot be identified.[103] Finally, Bond et al. (2020) argue that the instrument used in the literature is not valid if revenue is used as the dependent variable and therefore the estimated output elasticity is inconsistent.[104]

35. The points raised by Bond et al. (2020) suggest fundamental critiques of the estimation approach in De Loecker, Eeckhout and Unger (2020) which may

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[100] This is a simultaneity bias. The error term is correlated with the inputs and thus using OLS to estimate the production function coefficients is inconsistent.

[101] For example, see Olley, G., & Pakes, A. (1996), The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*;, Levinsohn, J. and Petrin, A. (2003), Estimating Production Functions Using Inputs to Control for Unobservables *Review of Economic Studies* 70: 317-342; or Ackerberg, D. A., K. Caves, and G. Frazer (2015), Identification properties of recent production function estimators, *Econometrica*, 83(6), 2411–2451.

[102] Bond et al. (2020) highlight additional issues which are important to consider. However, we focus here on the most relevant aspects to our analysis.

[103] While the first and third point are specific to the estimation approach, the second issue cuts across the two approaches we are considering.

[104] A recent paper by Kirov and Traina (2021) suggest overcoming the non-identification critique raised by Bond et al. (2020) by imposing structure on the scale elasticity and latent markup determinants. Traina, J., Kirov, I. (2021), Labor Market Power and Technological Change in US Manufacturing, Job Market Paper.

result in inconsistent estimates of the output elasticity and thus inconsistent estimates of the markup.

36. Recently, also De Ridder et al (2021)[105] have emphasised that it is essential to estimate markups using quantity rather than revenues. In fact, the average level of revenue-based markups is not informative of the true average markup. However, they also observe that the bias mainly affects the level of the markup because its dispersion is estimated reasonably well both in the cross-section and over time.

37. Finally, Raval (2020) highlights two additional issues in the production function approach:

(a) The estimated output elasticities depend on the variable cost that is used. Specifically, Raval (2020) use intermediate inputs instead of cost of sales and show that the elasticities differ.

(b) If productivity is labour augmenting, more productive firms will have different output elasticities of labour and materials than less productive firms. This heterogeneity implies that systematically different markups are estimated using alternative inputs.

38. Given the wide adoption of the production function approach in the literature, in the State of Competition report (2020) we committed to consider this methodology and the debate on De Loecker, Eeckhout and Unger (2020) in our future work. It is thus worth noting that De Loecker (2021)[106] discussed the critiques raised by Bond et al. (2020).

39. However, the recent debates indicate that there is still no consensus on how to implement the production function approach when the researcher has access to data on turnover and expenses rather than output and input quantities. For this reason and given the complexity of the various 'workarounds' currently debated, we have chosen not to use the production function approach at this stage.

Cost share estimation approach

40. The second approach we are considering approximates the output elasticity of an input factor by measuring that input factor's share of total variable costs (in our case, cost of sales as a share of total variable costs). This approach has

[105] De Ridder, M., Grassi, B., Morzenti, G. (2021), The Hitchhiker's Guide to Markup Estimation, Working Papers 677, IGIER, Bocconi University.
[106] De Loecker, J. (2021) Comment on Bond et al (2021), Journal of Monetary Economics, vol 121, 15-18.

been used in the literature, for example by De Loecker, Eeckhout and Unger (2020) in their sensitivity checks, Syverson (2004),[107] Foster et al. (2008),[108] Autor et al. (2020)[109] and Raval (2020) – who suggested a variant of the traditional approach we describe here.

41. Unlike the production function approach, the cost share approach does not require the specification of a production function. However, it makes two additional assumptions: that the first order condition for cost minimisation holds for all inputs in any given year, including those that require a cost adjustment (at least on average across all firms in a given industry); and, perhaps more importantly, that firms have constant returns to scale, ie that the marginal cost of producing a product does not vary with the amount produced.

42. Under these two assumptions, output elasticities can be estimated based on data on revenue and expenses, which is readily available in the FAME database. Following the recent literature, we measure the output elasticity as the average cost share in each 2-digit SIC code. More precisely:

$$\theta_{jt} = N_{jt}^{-1} \sum_{i \in j} \frac{P_{it}^{V} V_{it}}{P_{it}^{V} V_{it} + r_t K_{it}}$$

where θ_{jt} is the output elasticity in industry j at time t, N_{jt} is the number of firms in industry j at time t, P_{it}^{V} is the price of the input combination V of firm i at time t, and r_t is the user cost of capital K_{it} of firm i at time t.

43. We base our estimation of the elasticity on the following data. We measure the user cost of capital, r_t,[110] using the UK's interest rate, subtracting inflation and adding depreciation.[111] For depreciation, we assume a 12% rate, similar to De Loecker, Eeckhout and Unger (2020).

[107] Syverson, C. (2004) Market Structure and Productivity: A Concrete Example, NBER Working Paper No. 10501.
[108] Foster, L., Haltiwanger, J., Syverson, C. (2008), Reallocation, Firm Turnover, and Effiency: Selection on Productivity or Profitability?, American Economic Review 98(1), p. 394-425.
[109] Autor, D., Dorn, D., Katz, L. F., Patterson, C. Van Reenen, J. (2020), The Fall of the Labor Share and the Rise of Superstar Firms, The Quarterly Journal of Economics, 135(2), p. 645-709.
[110] This is consistent with the approach used in this academic literature and as noted in paragraph 20, the examination and discussion of cost of capital concepts within this report, and the use of specific cost of debt proxies, are intended only to provide broad context and aid debate. None of the concepts or estimation approaches discussed, nor the individual metrics used, are intended to reflect the CMA's view of best practice in the estimation of a cost of capital. Nothing in this report should be considered as relevant to any current or future CMA interpretation of a suitable level of, or measuring approach for, the cost of capital of any business or industry.
[111] We obtained the information on interest rates from the Bank of England and on inflation from the ONS.

44. For capital we used the fixed assets reported in our main specifications. However, this may not accurately reflect firms' capital stock. In the recent decades, intangible capital seems to have gained prominence (De Loecker and Collar-Wexler (2020)). With the ongoing digitalisation of the economy, fixed capital stock may not accurately reflect capital expenditures of firms. While we have intangible capital in the data, the interpretation of this variable is not clear cut. For example, intangible capital may include the brand value of an acquired brand, but not the value of the firm's own brand.[112] We consider that using fixed assets is a pragmatic approach for this report.[113] However, accurately capturing a firms' capital stock is a very important issue which may need further research.[114]

Weighting measures

45. After having estimated the markups for each firm in every year, we aggregate markups in order to compute for each year the economy-wide weighted mean markup.

46. The literature suggests different possible weighting measures reflecting companies' sizes. Following De Loecker, Eeckhout and Unger (2020) we use for our benchmark results turnover-based weights: specifically, we compute for each year the economy-level average markup by weighting each firm-level markup with their annual turnover.

47. In order to check the extent to which our results are driven by the weighting measure used, we also carried out some sensitivity checks by comparing the trend in the turnover-weighted mean markup (ie our benchmark) to the ones observed by applying other weighting measures.

48. Following De Loecker, Eeckhout and Unger (2020), we constructed two additional weighting measures:

(a) Employment weights, based on the number of employees of each firm

(b) Cost of goods sold (COGS) weights, based on the cost of sales of each firm deflated by the UK GDP deflator.[115]

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[112] For example, Coca Cola has a strong brand name, but this may not be reflected in its intangible capital.

[113] Please note that we also carried out a robustness check by using total assets and the results are in line with those we obtained by using fixed assets.

[114] De Loecker and Collar-Wexler (2020) recognise this issue, which also holds for the production function approach.

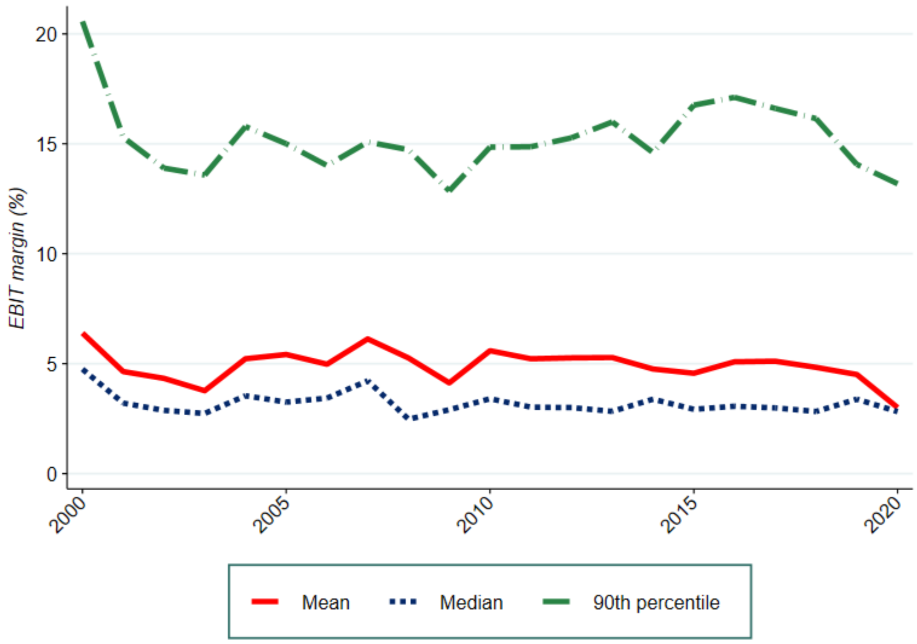
[115] Source: Gross domestic product at market prices:Implied deflator:SA - Office for National Statistics (ons.gov.uk).

49. The results presented in Chapter 4 show that the picture of the trend in the average markup over the period considered is very similar regardless of the weight used.

Profitability

50. As set out in paragraph 4.51 of Chapter 4, we conducted our EBIT analysis on firms who had information that allowed us to estimate both the markup and the EBIT. We were also able to conduct our analysis of EBIT margins using all firms for whom information on EBIT was available. This is reported in Figure C.1 below. When looking at the trends among this larger sample we see the same pattern.

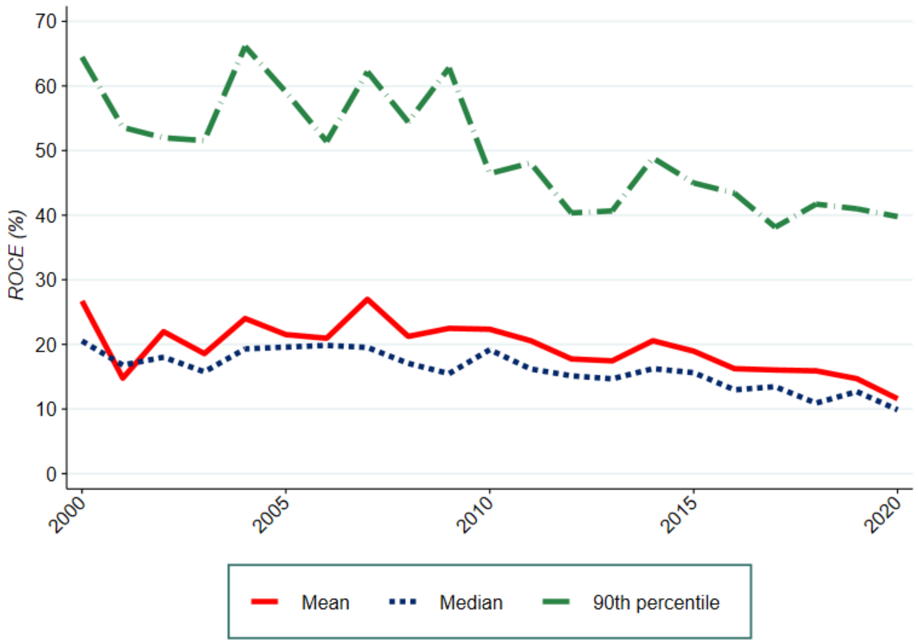
Figure C.1: Percentile distribution EBIT margin for large companies, different sample



Source: CMA analysis of FAME data

51. We also conducted our ROCE analysis on all firms who had ROCE information available. When looking at trends among this larger sample we see the same pattern, as shown in Figure C.2.

Figure C.2: Percentile distribution ROCE for large companies, different sample



Source: CMA analysis of FAME data

Cost of debt: measure used to benchmark CMA analysis of ROCE

Cost of capital

52. As set out in Chapter 4 of the main report, the trend in ROCE in the economy forms, conceptually, only half the story of the economic profits that UK businesses and their owners are earning. The other half is the 'opportunity cost' of the capital that is generating these returns. Businesses fund their capital employed through a mix of debt and equity, and there are costs associated with both of these sources of finance.

53. It is not possible to perfectly measure the opportunity cost of capital across the economy, so instead we have used an estimate of the cost of debt as a benchmark. This section explains the benchmark that we have used, and why we have chosen it. The examination and discussion of cost of capital concepts within this report, and the use of specific cost of debt proxies, are intended only to provide broad context and aid debate. None of the concepts or measuring approaches discussed, nor the individual metrics used, are intended to reflect the CMA's view of best practice in the estimation of a cost of capital. Nothing in this report should be considered as relevant to any current or future CMA interpretation of a suitable level of, or measuring approach for, the cost of capital of any business or industry.

54. The purpose of our estimate is to understand the context in which to consider the trends in ROCE that we have found. In order to do this, it is helpful for us to understand the direction of travel and some sense of the scale of trends in the cost of capital.

55. Conceptually, the cost of capital is made up of the cost of debt and the cost of equity. The cost of debt is largely observable. Business debt service costs, be it interest on bank loans or coupons on bonds, are largely unavoidable without placing a business into financial distress (in a similar way that consumers have to meet their mortgage or credit card payments). We can measure the average cost of debt either by looking at interest costs in company accounts or by using external benchmarks of debt costs.

56. The cost of equity is not a tangible cost that we can observe in company accounts, and so is much more difficult to measure accurately. Equity holders (be they private owners or shareholders of listed companies) generally only earn returns once the costs of debt have been paid, and risk receiving no return. However, in compensation for this additional risk, equity returns are not limited in the way that interest costs are.

57. As a result, the cost of equity is more 'conceptual', and can be described as the return that the owners *expect* to receive in order to compensate them for the risks associated with their investment. As such, without being able to ask every equity owner within a business what their expected return is – it can only ever be an estimated cost.[116]

58. While unexpected falls in interest (debt) rates may increase equity valuations in the short-term (and vice versa), over the long-term returns to debt and equity can reasonably be expected to trend in the same direction.[117] As we

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[116] The cost of equity is typically estimated using the Capital Asset Pricing Model, known at the CAPM. This model calculates the cost of equity in the following way: $Ke = Rf + \beta(Rm – Rf)$, where Ke is the cost of equity, Rf is the risk-free rate of return, β is beta, a specific investment's (or group of investments') relative exposure to systematic (undiversifiable) risk and Rm is the expected return of the 'market' (all relevant equity returns). This model attempts to estimate the cost of equity of a business (or group of similar businesses) by assessing the return available when taking little or no risk (Rf), and then calculating the additional return needed to encourage investment in equity (Rm-Rf) with a specific exposure to broad risks that can't be diversified away (β). As we can see from the CAPM equation, if we're trying to estimate the cost of equity for the whole of the UK, we may be able to reasonably assume that $\beta=1$ (beta is a measure of relative exposure to broad risks, which should be the same as the absolute exposure of the whole economy). On this basis, the equation simplifies to $Ke = Rm$, or the cost of equity is the expected returns to equity. In practical terms, we generally predict Rm using past returns (adjusted for inflation) and surveys of experts as a guide to what equity investors reasonably expect to earn. However, actual future equity returns are unknowable and are likely to be subject to a range of exogenous shocks and unforeseen events (for example, aggregate UK equity returns in the last two decades are likely to have been influenced by issues such as the global financial crisis, Brexit and the impact of the pandemic – issues that are unlikely to have been anticipated in advance).

[117] Lower discount rates may increase the net present value of future cashflows when measured today (and so increase the current 'price' of equity), but without higher growth prospects this return is largely 'brought forward' - reducing returns in future periods. Lower discount rates are also associated with lower future growth, which may exacerbate the reduction in future returns.

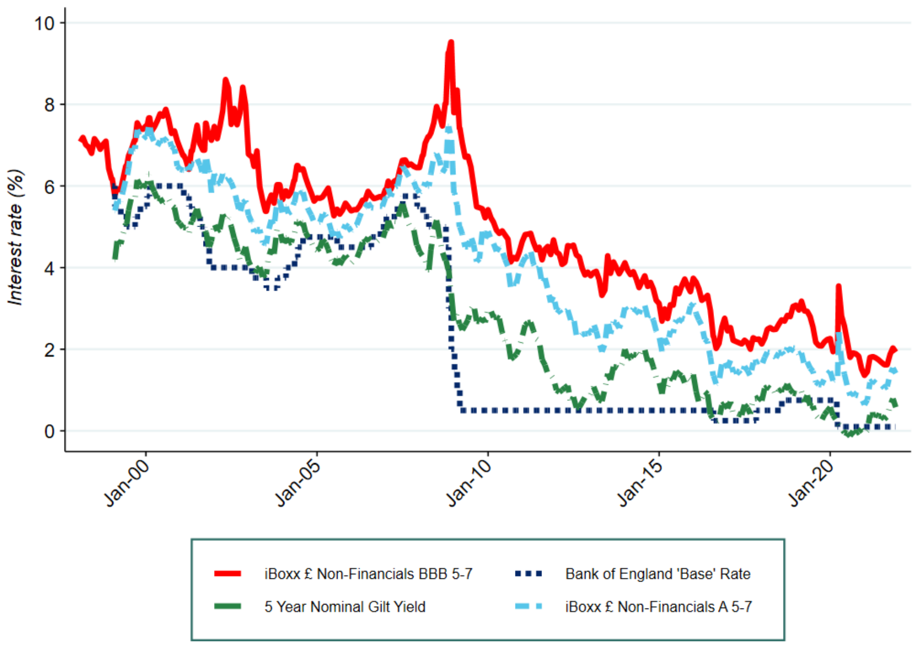
are looking for aggregate trends rather than trying to assess the exact difference or ratio between ROCE and the cost of capital, we will use trends in the (observable) cost of debt to infer trends in the overall cost of capital in the economy.

Cost of debt

59. When assessing the overall cost of capital in the economy, we look at broad trends in debt metrics.

60. Figure C.3 shows the Bank of England base rate,[118] which is commonly used as a reference rate for bank loan pricing, the effective interest rate (yield) on 5-year nominal UK government bonds (known as gilts, longer maturities of which are often used as a proxy for the 'risk-free' rate of return), as well as the yields on indices of A-rated and BBB-rated UK non-financial debt at similar maturities.[119]

Figure C.3: Proxies for (and inputs into) average borrowing costs since 1999



Source: CMA analysis of Bank of England and iBoxx data

118 Since 2006 the 'Official Bank Rate' and prior to this the 'Repo Rate'.

119 'A' and 'BBB' are investment grade debt, considered appropriate for a range of investors and with limited risk of default. 'BB' or lower credit ratings are known as 'high yield' or 'junk' bonds and are considered to have higher risks of default. Relatively few companies have 'AA' or 'AAA' ratings currently. In Figure 3, the current average maturity of instruments in both the A-rated and BBB-rated index is 5.8 years.

61. While only indicative of borrowing costs faced by the wider spectrum of UK companies, the chart does show a reasonably consistent trend across measures of debt costs over time. Borrowing costs appear broadly stable with some fluctuation during the late 1990s and most of the 2000s.

62. This relative stability was interrupted by the global financial crisis in 2008 – with business debt costs rising as investors' perception of risks rose and, conversely, government borrowing costs falling, potentially as a result of a 'flight to safety' as investors looked to protect their capital by investing in lower-risk instruments. We can also see the monetary policy reaction to the crisis, with the Bank of England slashing its base rate in 2008 and 2009, with little in the way of increases since

63. Since the peak of the global financial crisis, we have seen a steady decline across these indicators of borrowing costs, although with a slight increase through late 2017 and into 2020.

64. While the path varies from year to year, the overall trend shows a distinct fall in all borrowing cost indicators over the period. The debt cost indicators in Figure C.3 to have fallen by between 3 and 5 percentage points over the last two decades.[120] If we make the assumption that costs of equity have moved in at least the same direction (and actual UK-listed equity total returns have lagged the long-term average over the last 20 years),[121] we can better contextualise the decrease in turnover-weighted mean ROCE we observe (see Figure 4.11 in Chapter 4) over the last two decades.

65. In our analysis which is set out in Chapter 4, we have chosen the BBB trend line as our proxy for the cost of capital, as the companies making up BBB are likely to be more representative of the credit worthiness of those in the FAME dataset.[122] However, it is important to note that the companies in the BBB-rated index and those in the FAME dataset may still be very different. It is generally only larger and more established companies that issue listed bonds, with smaller and newer companies likely to use bank loans or other revolving or temporary credit facilities to meet their debt needs. Nevertheless, the fact that the trend in the cost of debt for BBB rated firms is in line with the other

[120] For the purposes of this exercise, we use nominal historic debt costs (not adjusted for inflation) in line with the nominal data used in our ROCE analysis.

[121] Actual CPI-real (adjusted for inflation) UK equity market total returns in the period between 1999 and 2020 averaged approximately 4% per year, and recent regulatory price controls have assumed estimates of real returns in the 6 to 7% range. However, it should be noted that equity returns tend to move in very long cycles, and a complete cycle may be around 20 to 30 years.

[122] In addition, bond yields at lower 'junk' credit ratings increased significantly in the global financial crisis, which may not have been indicative of longer-term cost of capital trends.

measures of the cost of debt here, suggests that it is a reasonable measure to use for our purposes.

Appendix D: Other indicators of competition[123]

Introduction

0. This Appendix complements our work on other indicators of competition presented in Chapter 5.

1. Dynamic measures of market structure go beyond what static measures such as concentration can tell us. In a well-functioning market, we would expect to see that the positions of top firms are contestable by other top firms and by newer entrants. We would also expect to see new firms entering the market and replacing incumbent firms which exit. If a lot of this dynamism is apparent in a market, then even a market with consistently highly concentration may, in fact, be competitive.

2. In measuring dynamic competition, there is a potentially limitless range of dynamic indicators which could be estimated – indicators can focus on different aspects of firm position (turnover, rank within industry, etc), and can be measured over different time ranges. In Chapter 5, we have focused on a small group of metrics which capture different aspects of dynamic competition. In this appendix, we provide some background and the sectorial breakdown for the following measures:

   (a) The rank persistence of the largest firms in each sector;

   (b) The rates of firm entry and exit; and

   (c) The evolution of market shares for different segments of the market.

Rank persistence

3. In Chapter 5, we introduced the concept of rank persistence. This measure captures the extent to which the largest firms in an industry are the same over time. This is an intuitive and simple way of considering dynamic competition. In a well-functioning competitive market, it may be expected that firms will shift in and out of the top positions over time.

[123] This work was produced using statistical data from ONS. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

Methodology

4. We chose a relatively simple approach to estimating the tendency of top firms to remain the same over time. The top ten firms by turnover within each sector in each year are identified and compared with the top ten firms three years previously. The number of firms which were in the top ten in both years is then counted. This approach parallels one used by Philippon in 'The Great Reversal', which counts the proportion of top ten firms which are in the same rank position as three years ago. [124]

5. In the BSD data, firms often change their primary SIC code from year to year. This reflects the fact that many large firms engage in multiple activities across different SIC codes, and which activity represents their primary business may change over time. In some contexts, this switching of SIC codes over time does not represent a problem (though the broader issue of the secondary activities of firms being excluded from the analysis is significant). In this metric, however, it is necessary to assign each firm to a single SIC code so the changes in firm ranking over time can be observed. This has been done by assigning each enterprise in the BSD to the SIC code in which they generated the most turnover over the whole time period.

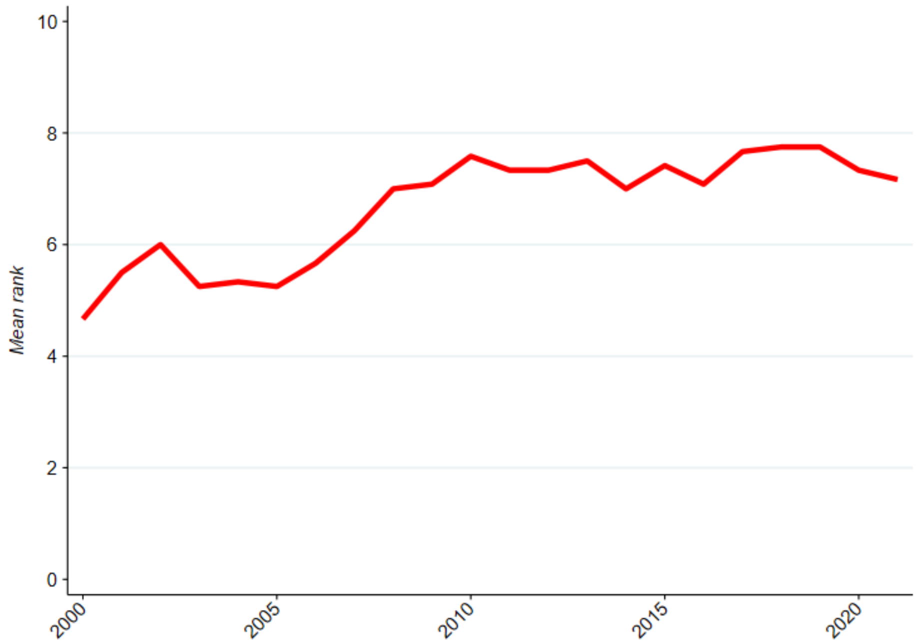
Sector-level results

6. Figure 5.1 in Chapter 5, replicated here in Figure D.1, presented the simple average across sectors of the number of top ten firms which were also top ten firms three years previously, over time.

7. An overall increase in rank persistence over time is visible. Among the top ten firms in 2000, there were only about five who were also among the top ten in 1998. This number increased to over seven in 2021. The increase in rank persistence occurred mainly in the second half of the 2000s.

[124] Philippon, T. (2019), *The Great Reversal: How America Gave Up On Free Markets,* Harvard University Press.

Figure D.1: Rank persistence over three years of top ten firms in each sector



Source: CMA analysis of ONS BSD data
Note: rank persistence is first calculated at sector level and then averaged across sectors without the use of any weight. Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example 'Activities of religious/political/trade union organisations', and 'Activities of households as employers of domestic personnel'. The 4-digit industry 'Wholesale of solid; liquid and gaseous fuels and related products' and several as its turnover disproportionate affects our results.

8. Figure D.2 to Figure D.13 show the underlying sector breakdown. They show the numbers of top ten firms in each sector which were also top ten firms three years previously in each sector over time. There are different dynamics, but as highlighted in Chapter 5, for example

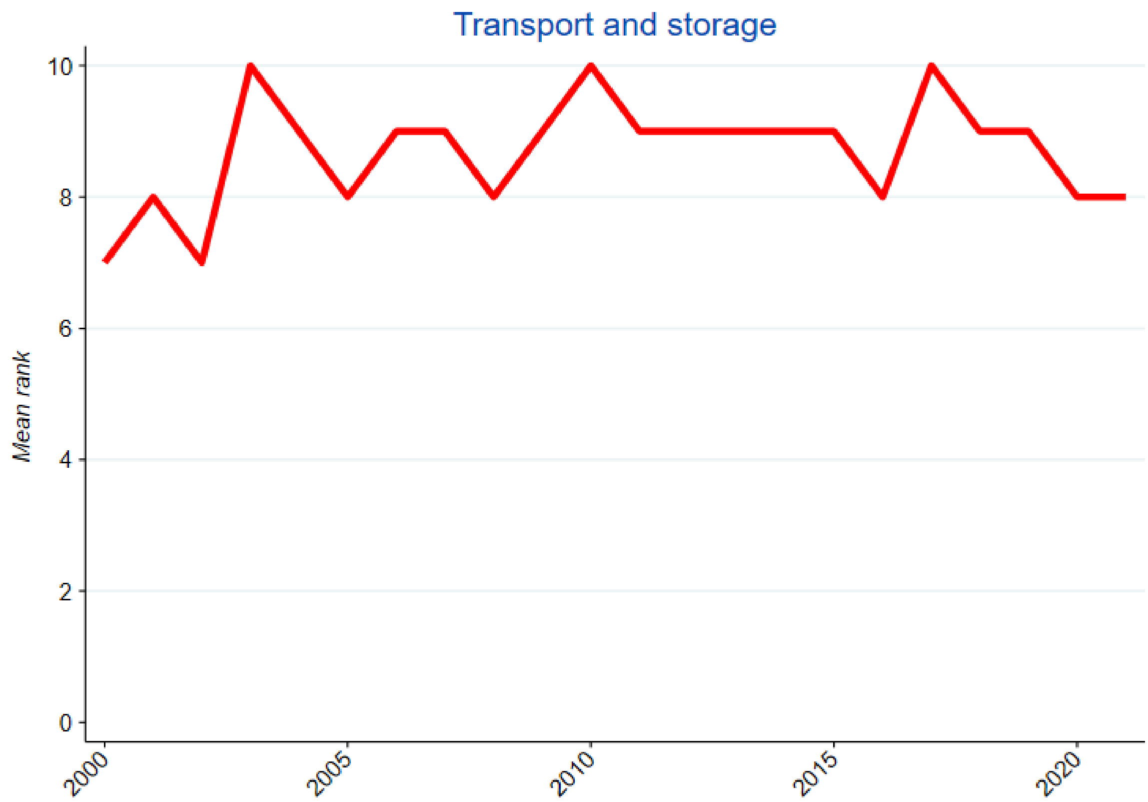
(a) Professional and scientific services and Finance and insurance sectors presented particularly large increases. These sectors saw rank persistence as low as one in the early years of the time series, but consistently above five and sometimes as high as eight or nine in later years.

(b) Several prominent sectors observed high rank persistence over the most recent ten years, including Wholesale and retail trade, Transport and storage, and Information and communication, all of which had rank persistence of nine in several years, indicating a great deal of stability in the identities of the top businesses in the sector.

Figure D.2: Mean rank persistence over three years in Wholesale and retail trade

Source: CMA analysis of ONS BSD data
Note: The 4-digit industry 'Wholesale of solid; liquid and gaseous fuels and related products' and several as its turnover disproportionate affects our results.

Figure D.3: Mean rank persistence over three years in Transport and storage

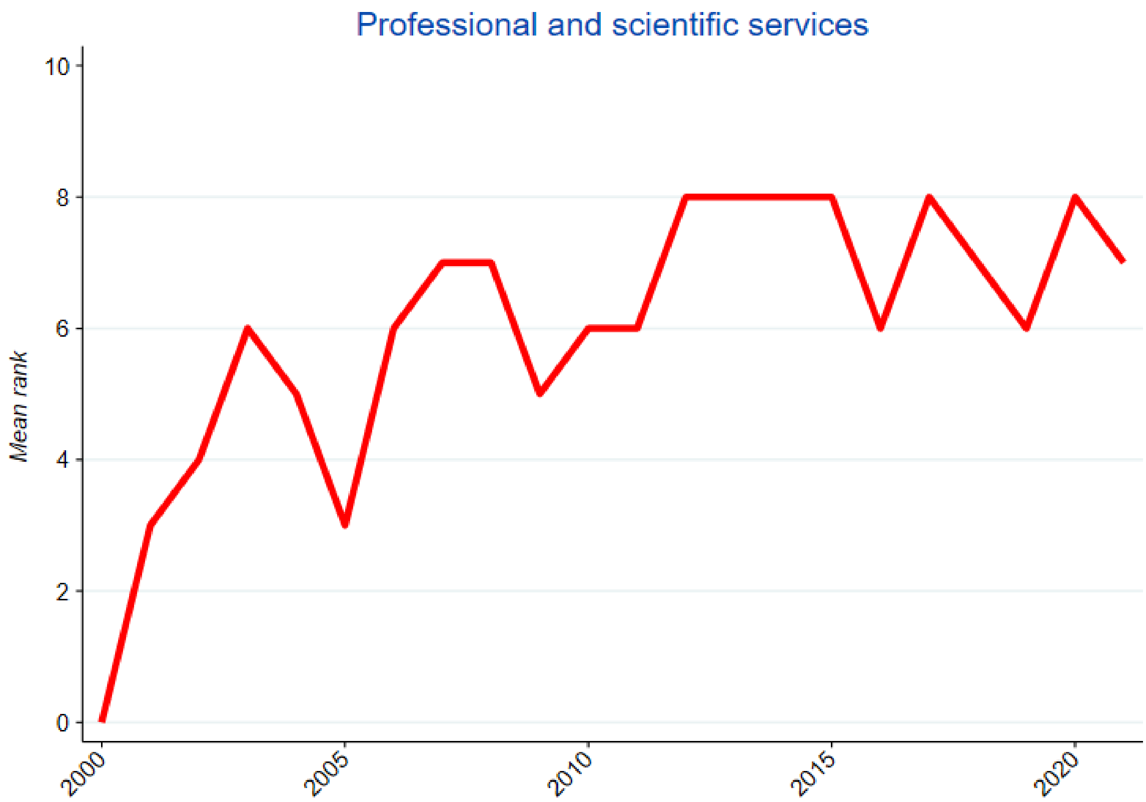


Source: CMA analysis of ONS BSD data

Figure D.4: Mean rank persistence over three years in Real estate activities

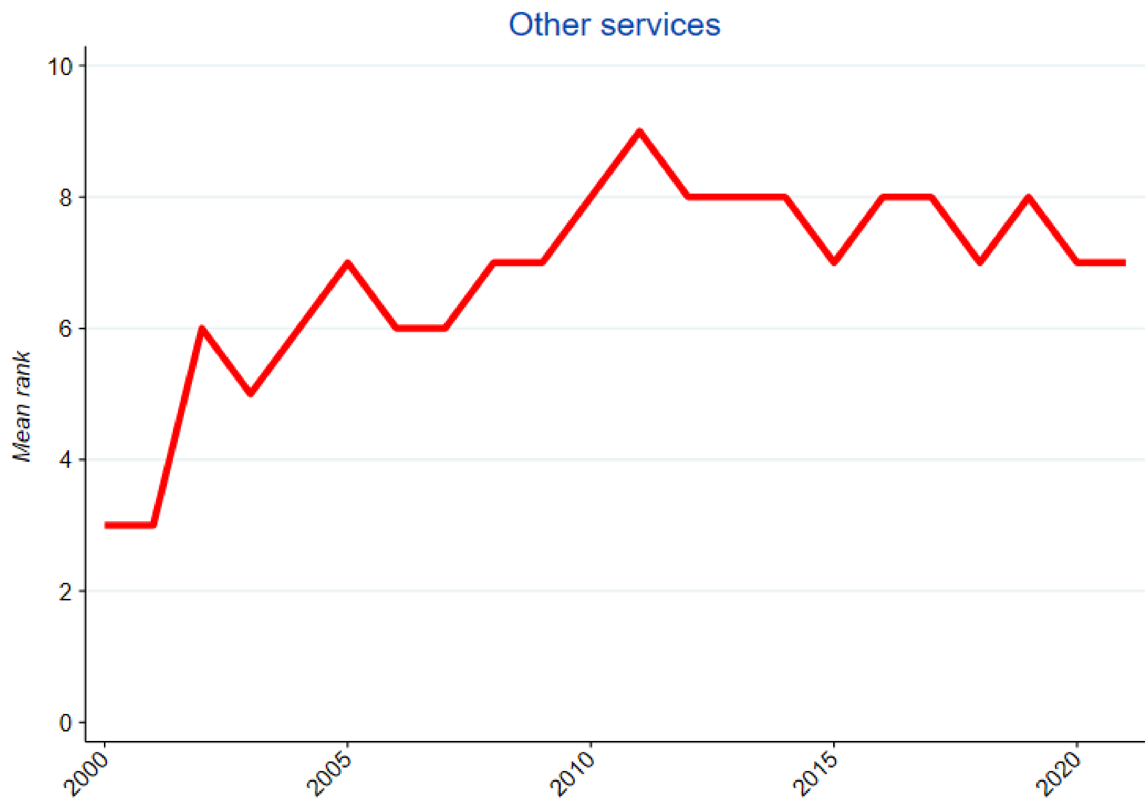
Source: CMA analysis of BSD

Figure D.5 Mean rank persistence over three years in Professional and scientific services



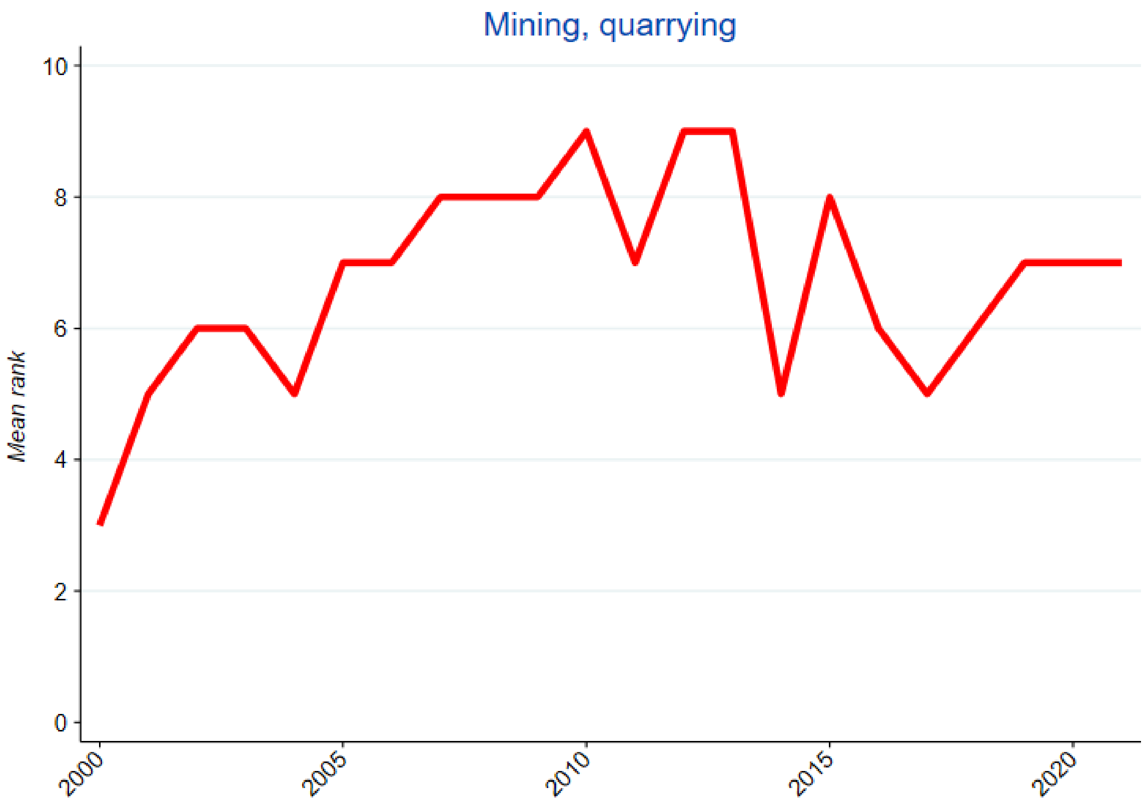
Source: CMA analysis of ONS BSD data

Figure D.6: Mean rank persistence over three years in Other services



Source: CMA analysis of ONS BSD data
Note: We have excluded several non-market 4-digit SIC industries, for example 'Activities of religious/political/trade union organisations', and 'Activities of households as employers of domestic personnel'. The 4-digit industry 'Wholesale of solid; liquid and gaseous fuels and related products' and several as its turnover disproportionate affects our results.

Figure D.7: Mean rank persistence over three years in Mining, quarrying

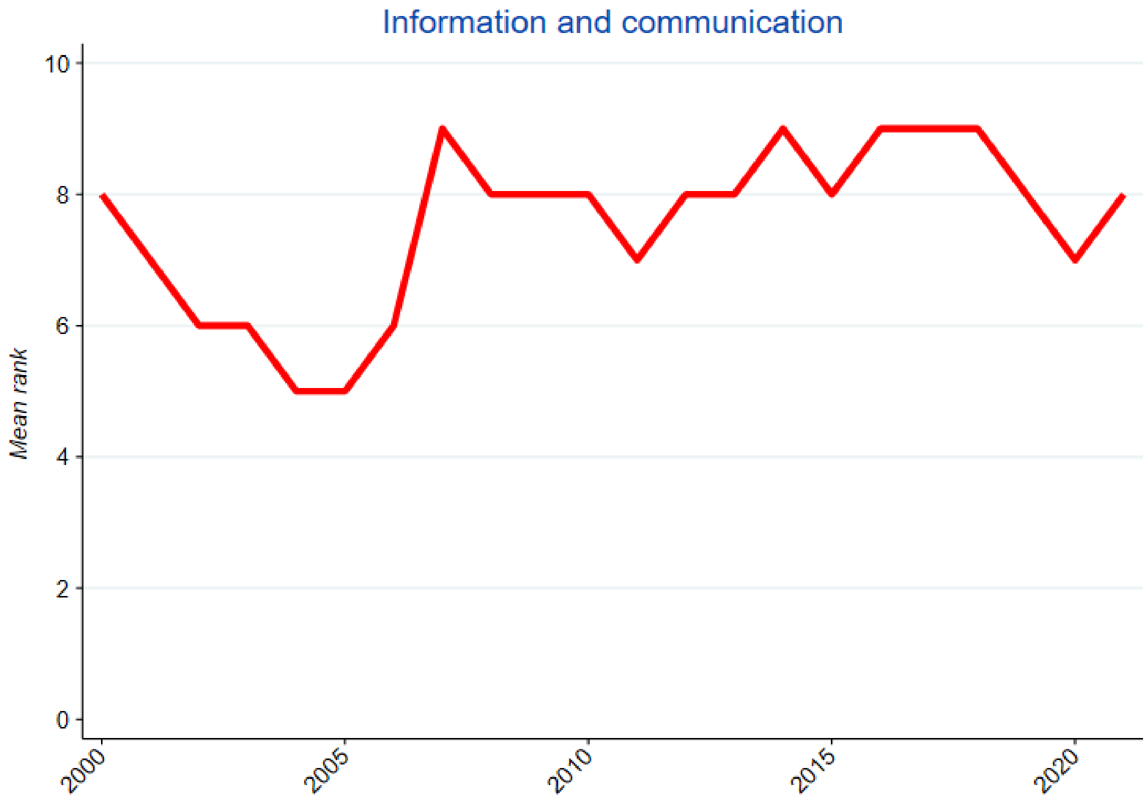


Source: CMA analysis of ONS BSD data

Figure D.8: Mean rank persistence over three years in Manufacturing

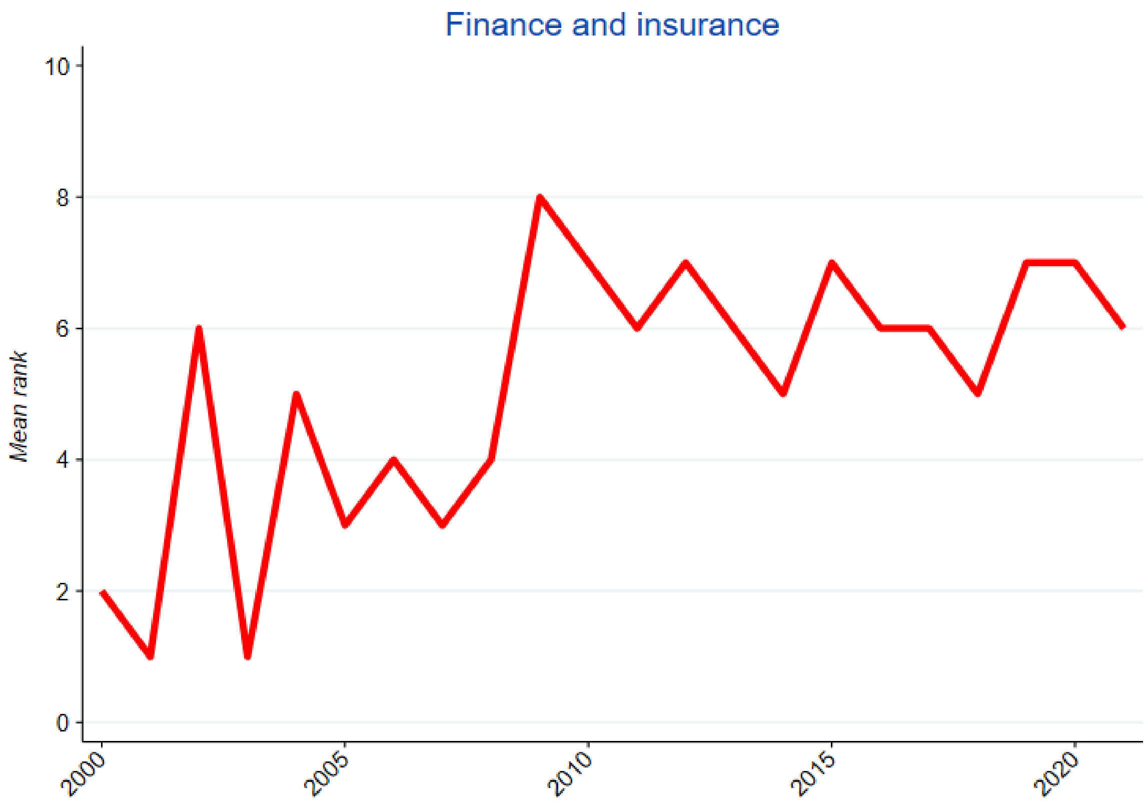
Source: CMA analysis of ONS BSD data

Figure D.9: Mean rank persistence over three years in Information and communication



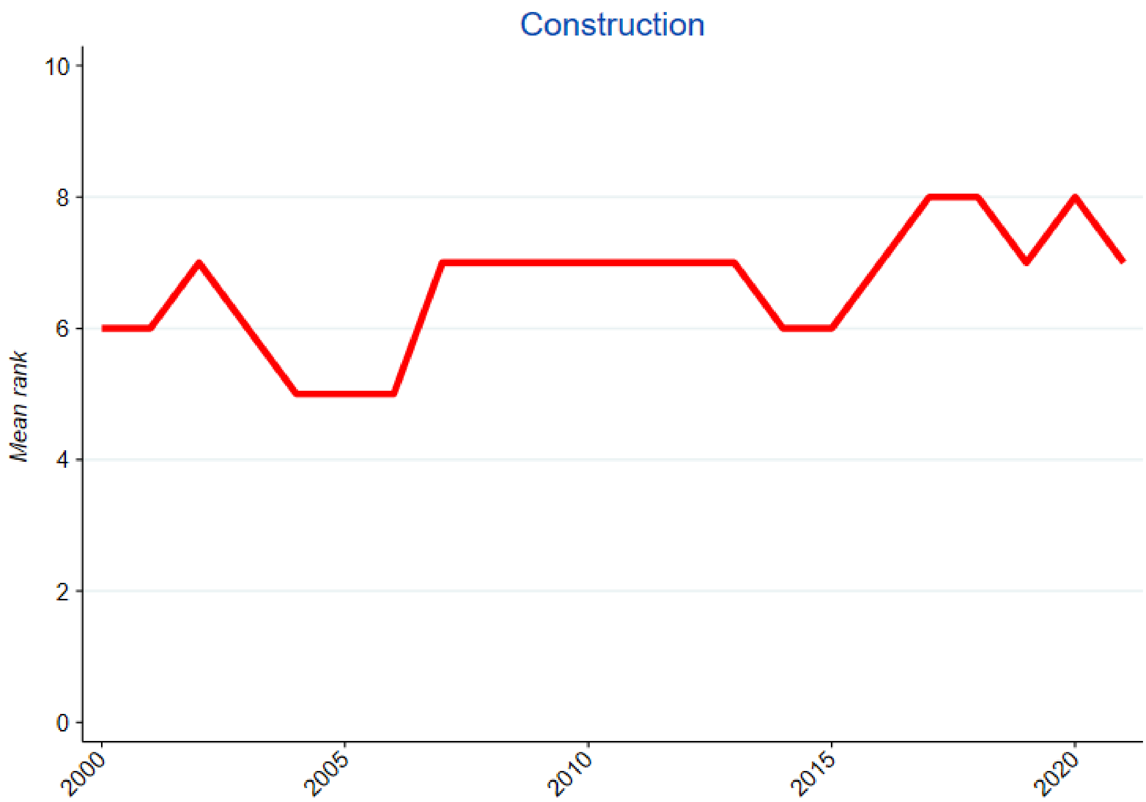
Source: CMA analysis of ONS BSD data

Figure D.10: Mean rank persistence over three years in Finance and insurance



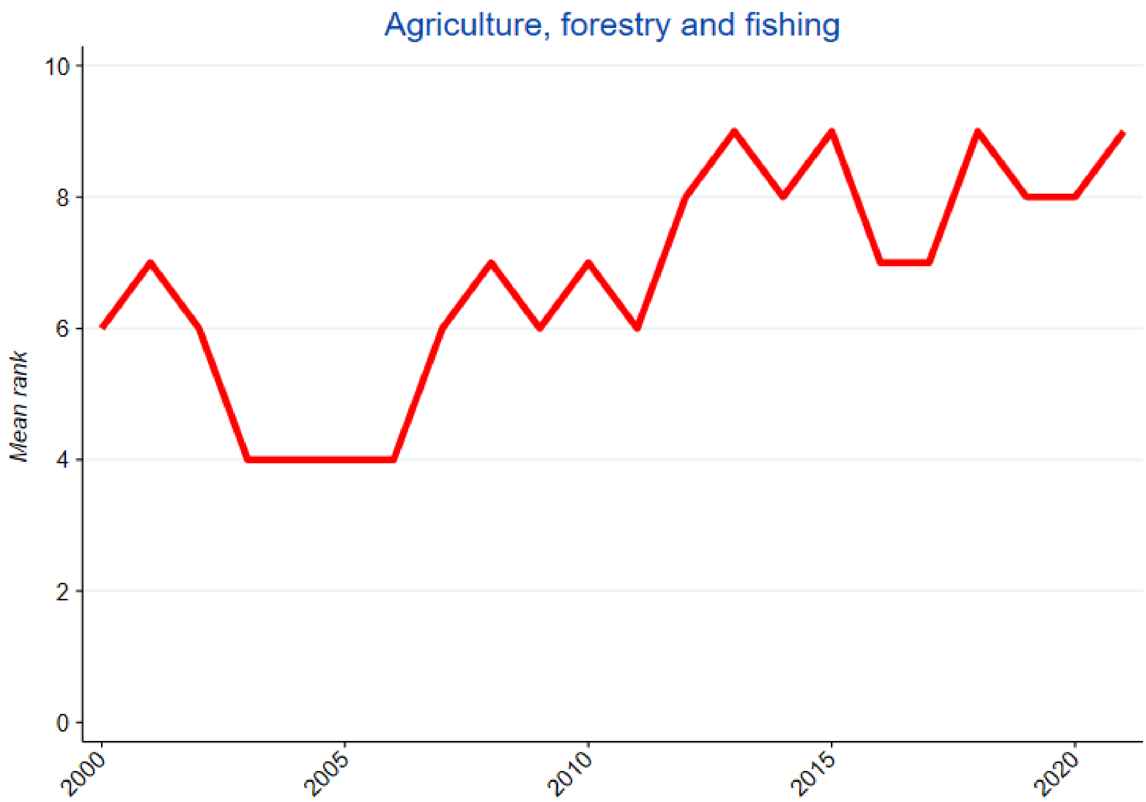
Source: CMA analysis of ONS BSD data

Figure D.11: Mean rank persistence over three years in Construction



Source: CMA analysis of ONS BSD data

Figure D.12: Mean rank persistence over three years in Agriculture, forestry and fishing



Source: CMA analysis of ONS BSD data

Figure D.13: Mean rank persistence over three years in Accommodation and food services

Source: CMA analysis of ONS BSD data

Entry and exit rates

9. The most widely used dynamic measures of competition are the rates of entry and exit. The link between firm exits and the level of competition is more indirect. In a well-functioning market with healthy level of firm entry, it may be expected that less efficient firms will exit the market as they are replaced and outcompeted by more efficient firms.

10. However, high entry and exit do not necessarily indicate dynamism; it could be the case that new firms are failing to challenge the incumbent firms, and the firms which exit represent recent (effectively failed) entrants rather than older, less efficient firms. In addition, entry and exit rates may not tell us much about dynamism in parts of markets occupied by large firms, as the entry and exit of larger firms will be overwhelmed in the statistics by small firms (which is why we also consider metrics focused on larger firms). Finally, the exit of too many firms from a market may lead to there being too few firms remaining

to sustain strong competition; this is especially likely to be the case where firm exits are caused by external factors such as financial crises.

11. It is also worth noting how the way in which the BSD database works may affect the measurement of entry and exit rates. The entry and exit rates we calculated can only measure instances when entire enterprises are established and dissolved. Entry into a market by a firm already operating in another market, or exit by a firm that continues to operate in another market will not be captured by these measures because they do not result in the formation or closure of a recorded enterprise.

Methodology

12. The BSD records the dates of the formation and closure for each of the enterprises on the dataset. The number of recorded entrants and exiting enterprises in each year may be counted and divided by the number of active enterprises in that year to give percentage rates of entry and exit. Often, firms become inactive (and so effectively exit even though an enterprise is not removed from the BSD) but this technique does not take account of whether firms are active or inactive, in contrast to other metrics estimated in this report which only include active firms.[125] For this reason, entry rates tend to be consistently higher than exit rates.

13. While the static concentration analysis groups enterprises recorded on the BSD into enterprise groups, this correction is not used in the dynamic analysis. This is because it is not possible to consistently and accurately trace the ownership of enterprise groups over time due to events such as mergers and takeovers.[126] This means that the continuity of ownership of a given enterprise or enterprise group may be unclear over time. This may bias the results, though it is not clear in which direction.

Sector level results

14. Figure 5.6 in Chapter 5 showed the economy wide entry and exit rates. In Figure D.14 and Figure D.15 below we show the entry rates for the higher and lower-turnover sectors.

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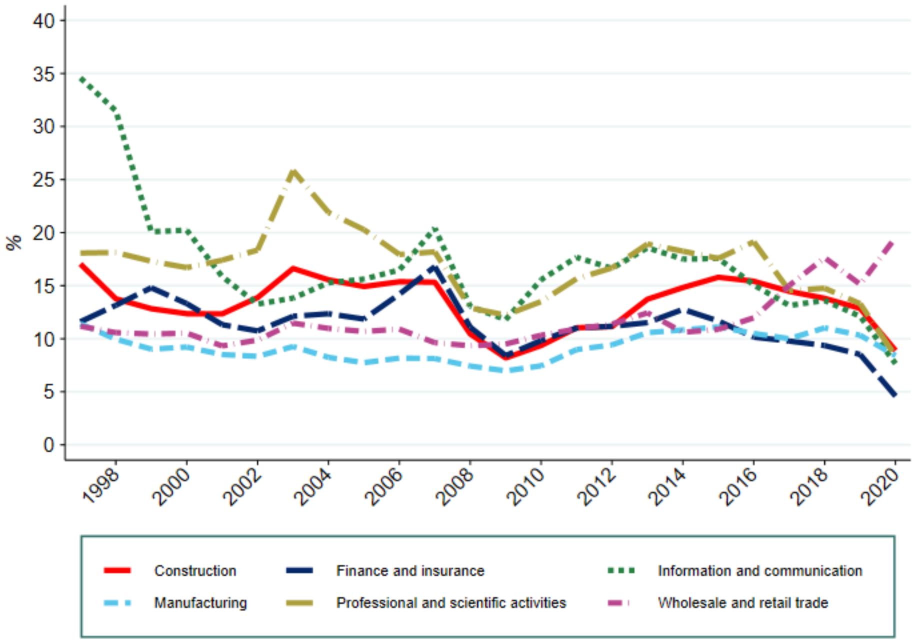
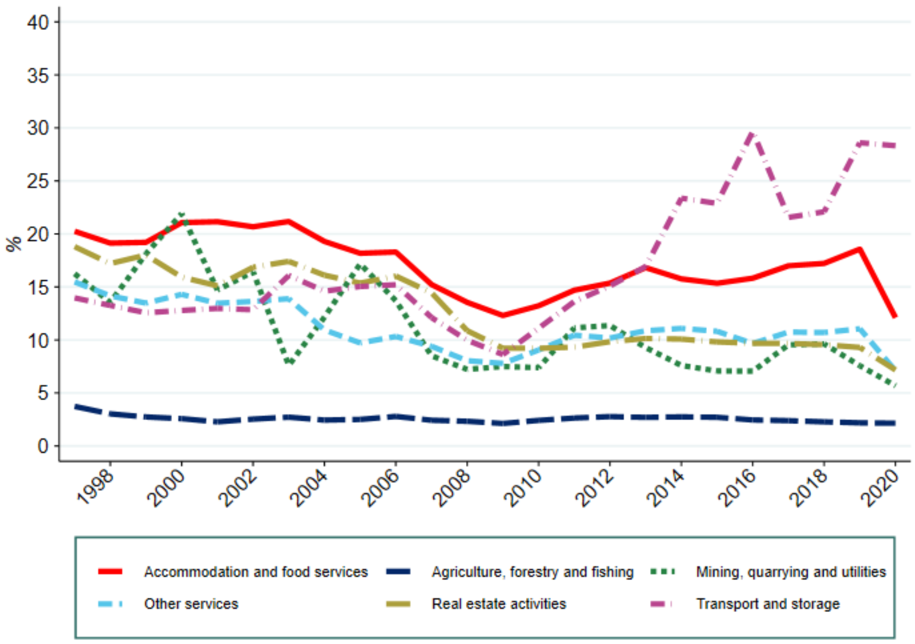
[125] An alternative methodology which relied on the first and last years when an enterprise was recorded as being active in the BSD was also used to calculate entry and exit rates. The same trends in entry and exit rates are apparent. This methodology was not chosen as the primary one because it appears to be noisier, reflecting the data lags which can occur from the way in which the BSD is updated each year.
[126] Demographic events such as these are not consistently identified in the BSD, preventing the estimate of ownership-corrected dynamic measures.

Figure D.14: Entry rates, higher-turnover sectors



Source: CMA analysis of ONS BSD data
Note: Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example 'Activities of religious/political/trade union organisations', and 'Activities of households as employers of domestic personnel'. The 4-digit industry 'Wholesale of solid; liquid and gaseous fuels and related products' and several as its turnover disproportionate affects our results.

Figure D.15: Entry rates, lower-turnover sectors



Source: CMA analysis of ONS BSD data
Note: Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because

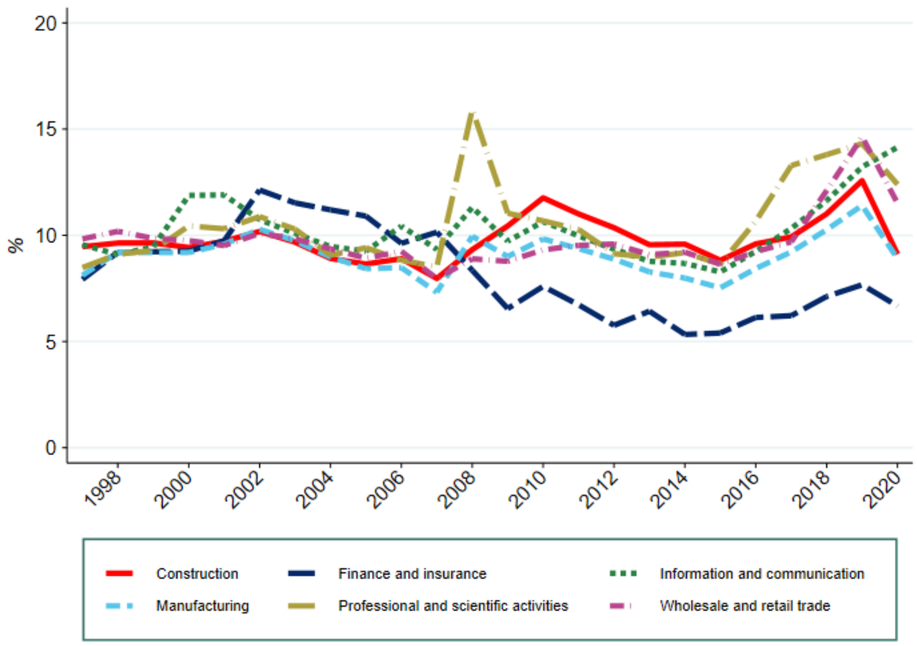
they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example 'Activities of religious/political/trade union organisations', and 'Activities of households as employers of domestic personnel'.

15. In the sector-level entry rates we can see that the decrease in the economy-wide entry rate during the financial crisis was driven by a particular group of sectors – Information and communication; Professional, scientific and technical services; Finance and insurance; and Construction. The first two have notably high rates of entry earlier on in the time series. Manufacturing maintained very stable entry rates over time (though lower than other large sectors), without any significant dip being observed during the financial crisis. Wholesale and retail trade saw an increase in entry since 2015.

16. Among the lower-turnover sectors, there are varied trends including several sectors which experienced a decline in entry rates following the financial crisis (eg Real estate activities). Transport and storage experienced higher entry rates in the years following the financial crisis. The entry rate in Agriculture, forestry and fishing is consistently low compared to other sectors.

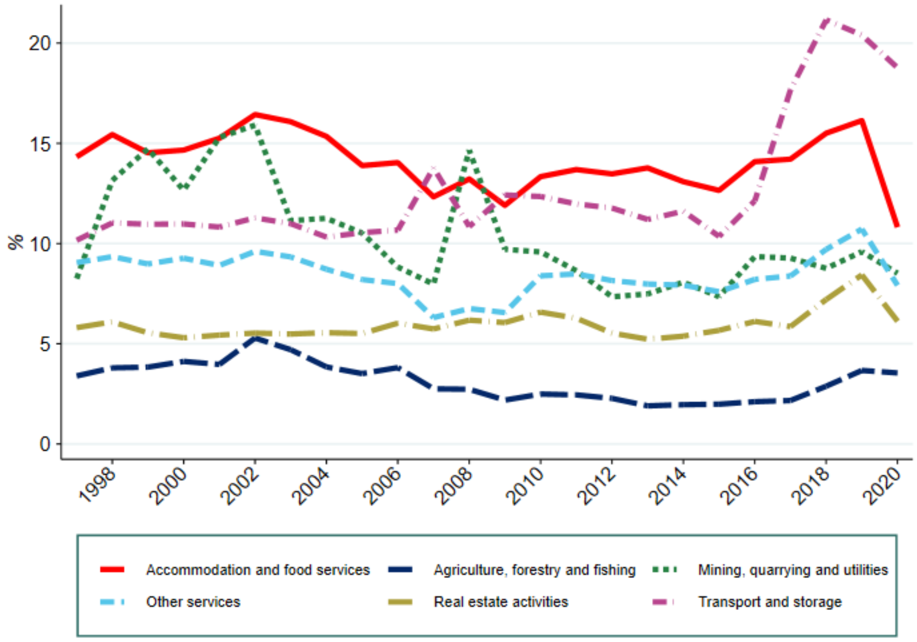
17. In Figure D.16 and Figure D.17 below we show the exit rates for the higher and lower-turnover sectors.

Figure D.16: Exit rates, higher-turnover sectors



Source: CMA analysis of ONS BSD data
Note: Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example 'Activities of religious/political/trade union organisations', and 'Activities of households as employers of domestic personnel'. The 4-digit industry 'Wholesale of solid; liquid and gaseous fuels and related products' and several as its turnover disproportionate affects our results.

Figure D.17: Exit rates, lower-turnover sectors



Source: CMA analysis of ONS BSD data
Note: Public administration and defence; compulsory social service, Education, and Human health and social work sectors have been excluded as they are dominated by the public sector; and Electricity and water supply have been excluded because they are highly regulated. We have also excluded several non-market 4-digit SIC industries, for example 'Activities of religious/political/trade union organisations', and 'Activities of households as employers of domestic personnel'.

18. Among higher-turnover sectors, exit rates are relatively similar and stable over time for the early part of the time series. Professional, scientific and technical services experienced a large spike in its exit rate during the financial crisis, and Information and Communication a smaller increase. Finance and insurance had a relatively high exit rate in the years prior to the financial crisis, falling to a level below that of the other higher-turnover sectors afterwards. Most sectors increased their exit rates since 2015.

19. Exit rates among the lower-turnover sectors are far more varied. Accommodation and Food Services consistently had the highest or near-highest exit rate of all sectors, followed by Mining and quarrying, and Transport and storage. The latter experienced a large rise in exits since 2016, which somewhat mirrors the increase in entry rates. Real estate activities, and Agriculture, forestry and fishing consistently had the two lowest exit rates.

20. Overall, at the whole economy level, entry and exit rates appear to be cyclical – with entry decreasing and exits spiking during the financial crisis. The individual sector trends show that these cyclical trends are driven by only

some sectors. The large variability between the entry and exit rates of different sectors is also notable.

Evolution of market shares

21. In Chapter 5, we have shown the evolution of average market shares for the five largest companies in each industry and those outside the largest 20 since 1998, for three different sectors, namely Finance and insurance, Information and communication, and Accommodation and food services. Below, we show the same graphs for all sectors.

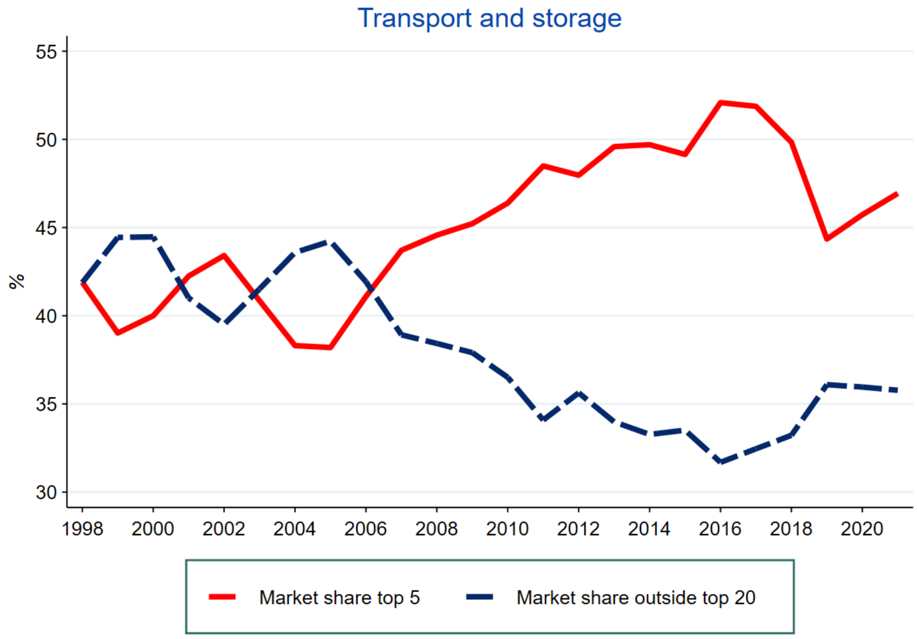
22. Overall, each sector presents its own dynamics. It is interesting to note that

(a) some sectors (eg Mining and quarrying, Manufacturing, and Finance and insurance) present high and stable (or even increasing) market shares for the top five companies.

(b) Others (eg Real estate activities, Professional and scientific activities, Other services and activities, Construction, Agriculture, forestry and fishing, Administrative and support services, and Accommodation and food services) present a relatively small and stable market share over time for the largest five companies.

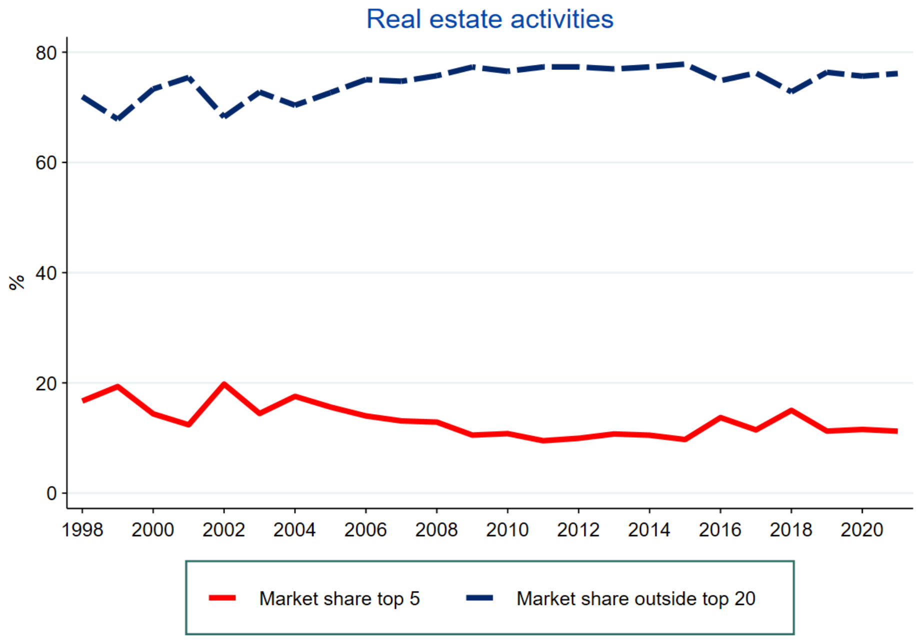
(c) Others, instead, show some market dynamics over time with the largest companies not always prevailing over the smaller ones (eg Transport and storage, Information and communication, Art, entertainment and recreation, and Wholesale and retail trade).

Figure D.18: Mean market shares in Transport and storage



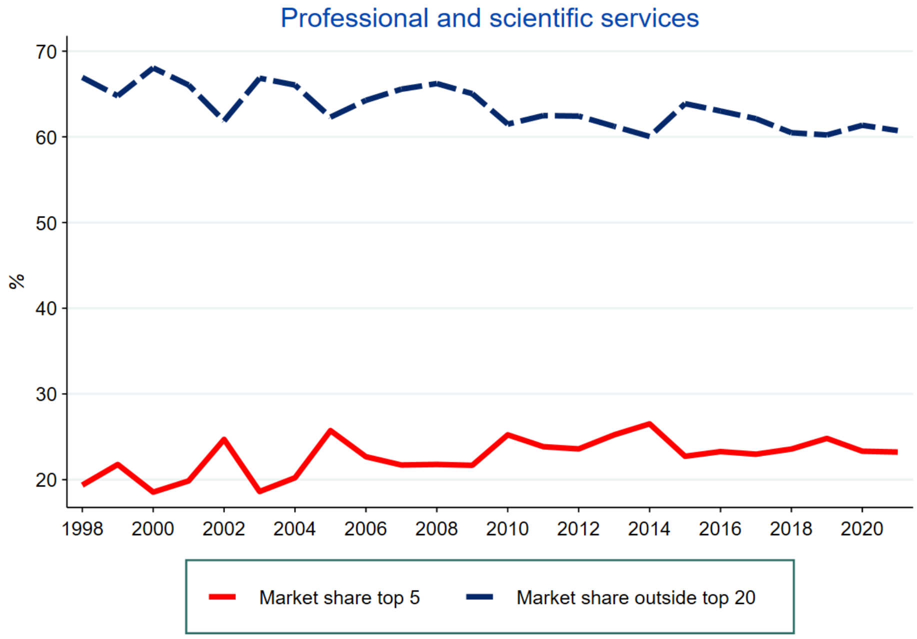
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.19: Mean market shares in Real estate activities



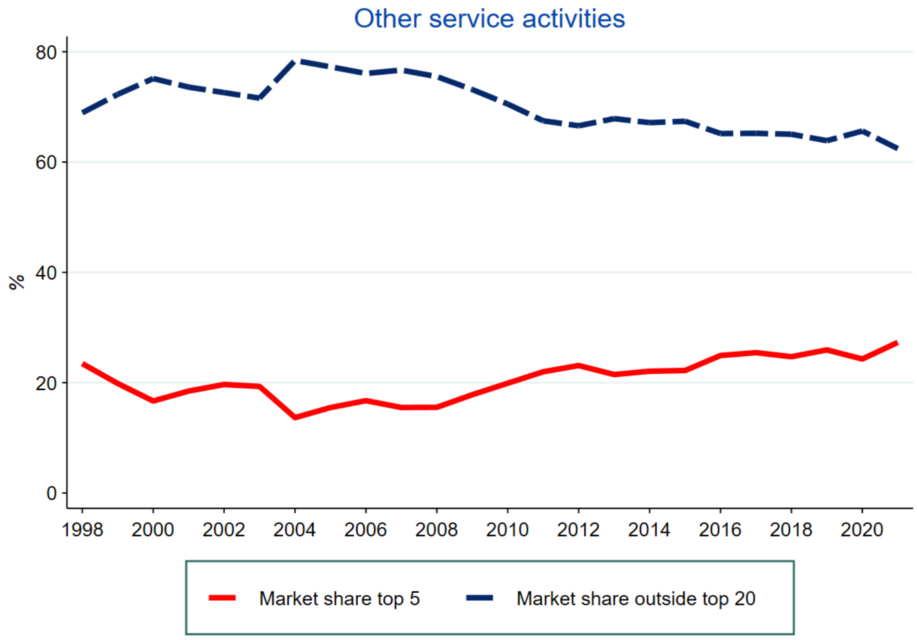
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.20: Mean market shares in Professional and scientific services



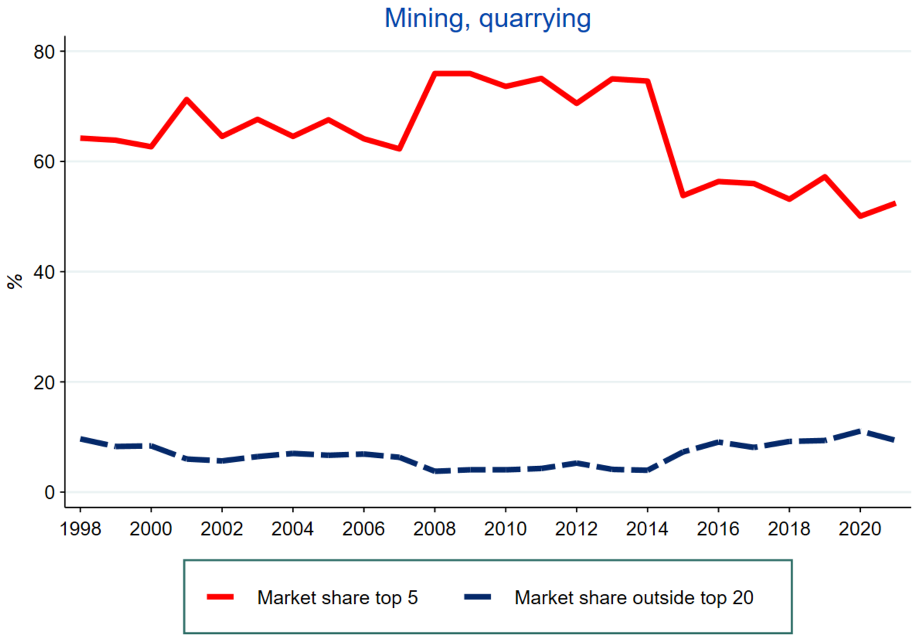
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.21: Mean market shares in Other service activities



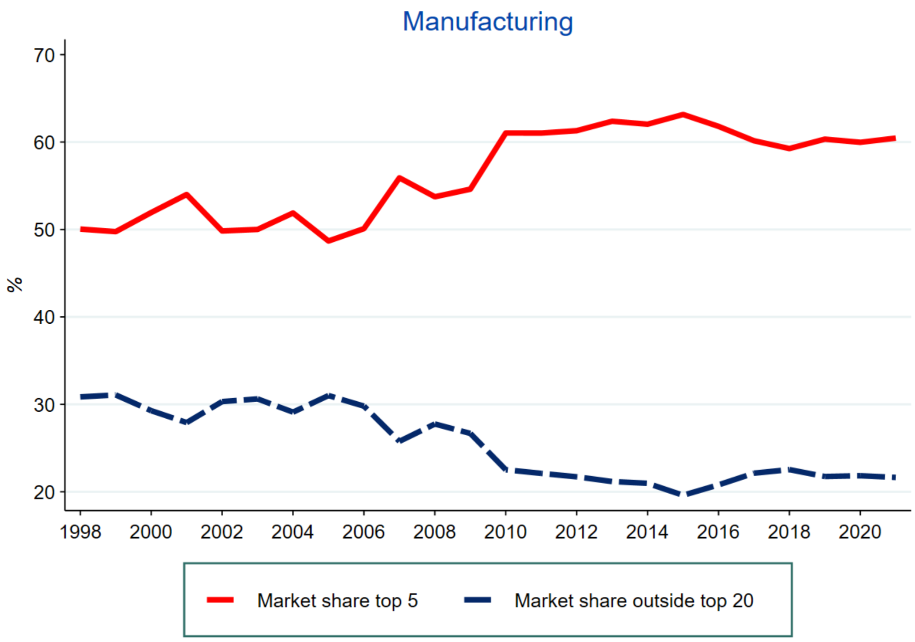
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.22: Mean market shares in Professional and Mining, quarrying



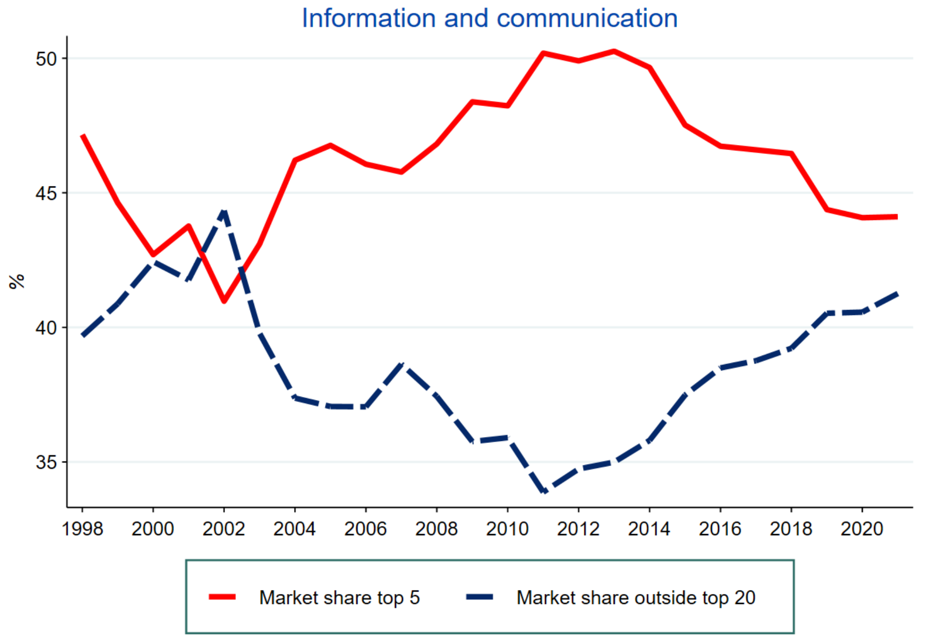
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.23: Mean market shares in Manufacturing



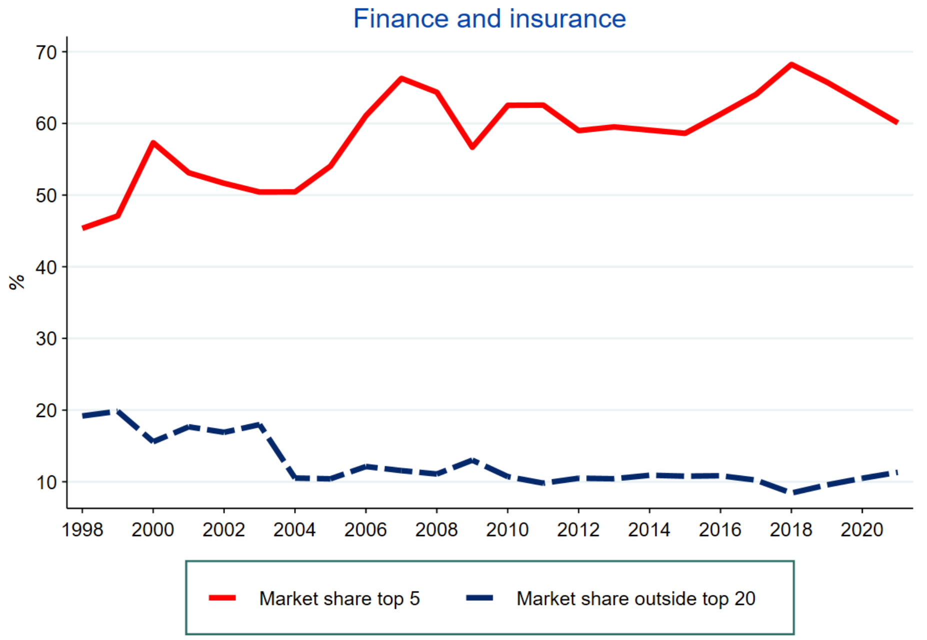
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.24: Mean market shares in Information and communication



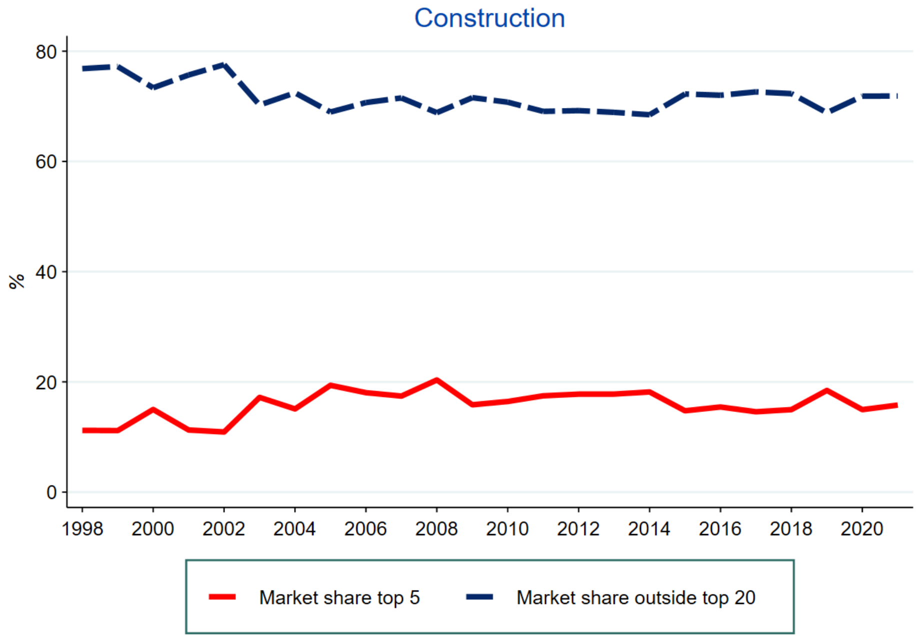
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.25: Mean market shares in Finance and insurance



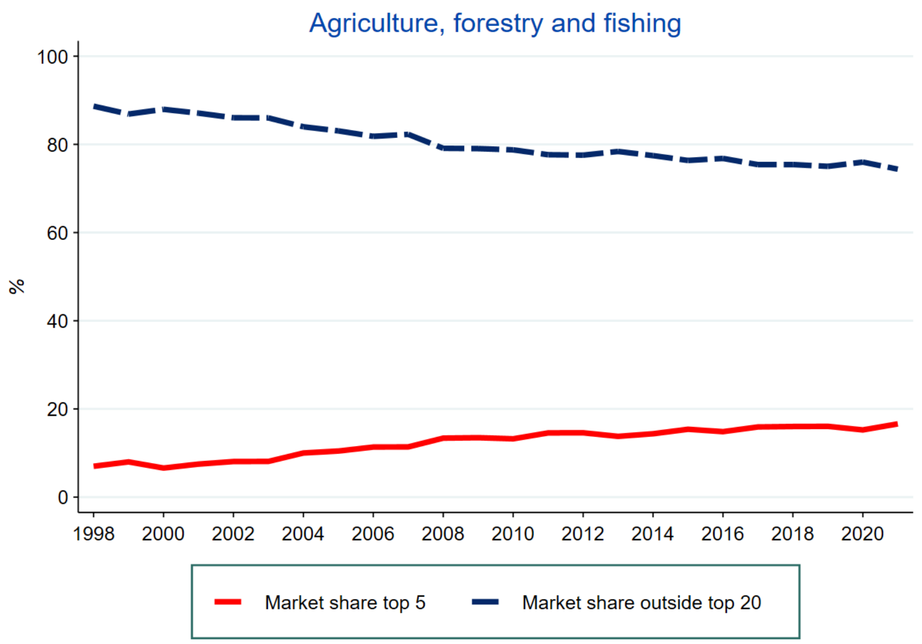
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.26: Mean market shares in Construction



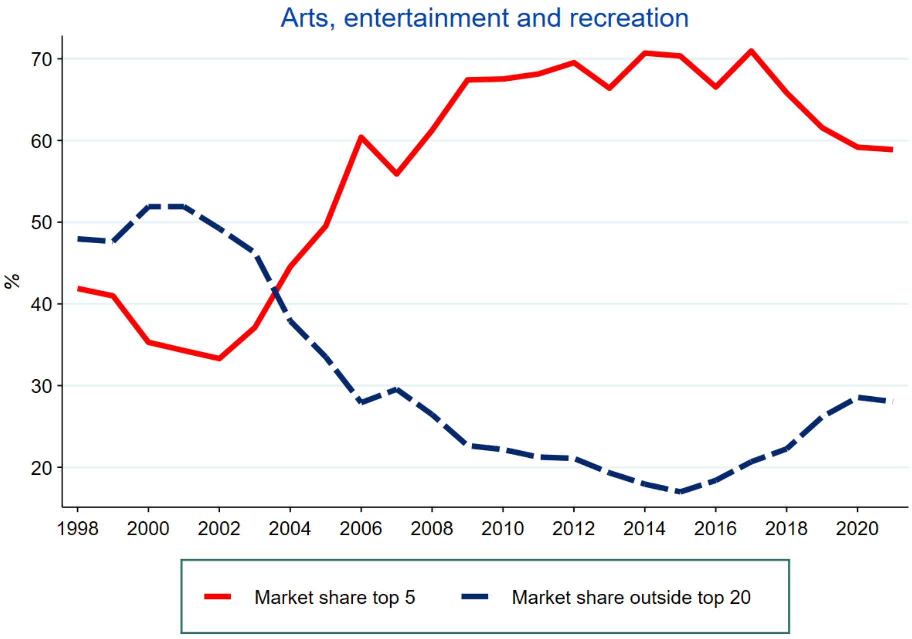
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.27: Mean market shares in Agriculture, forestry and fishing



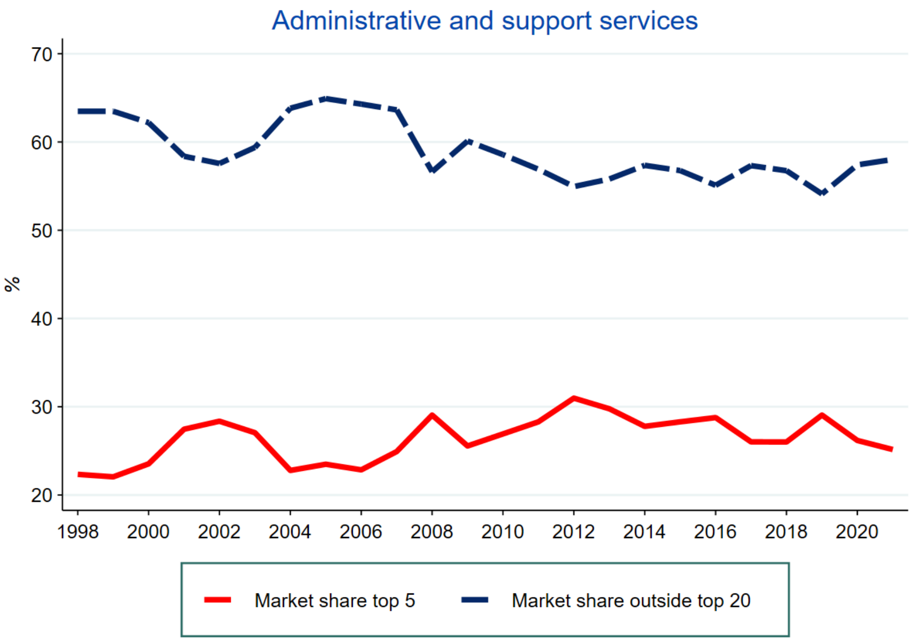
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.28: Mean market shares in Arts, entertainment and recreation



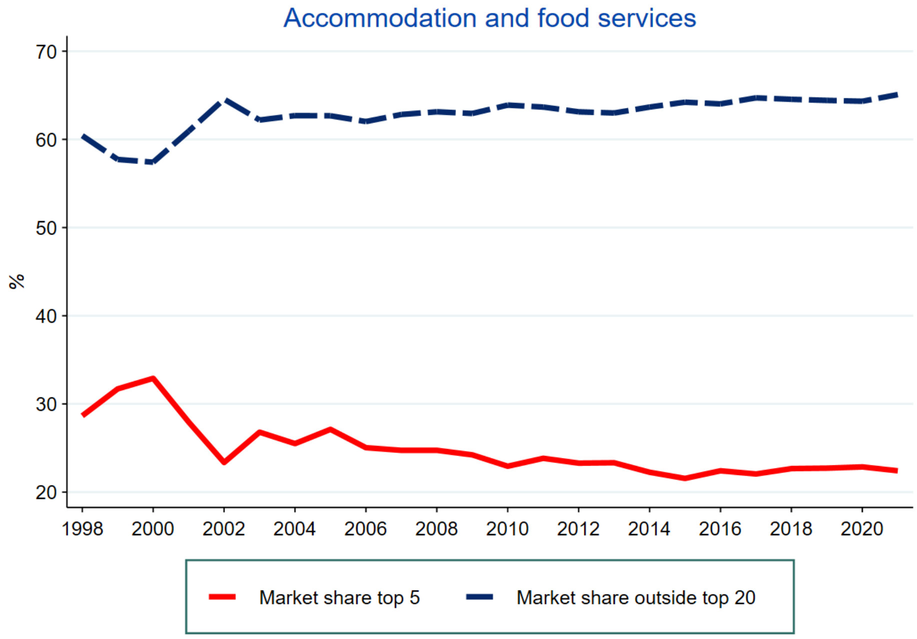
Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.29: Mean market shares in Administrative and support services



Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.30: Mean market shares in Accommodation and food services



Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights.

Figure D.31: Mean market shares in Wholesale and retail trade

Source: CMA analysis of ONS BSD data
Note: Market shares are calculated at 4-digit SIC industry level and averaged across the sector using turnover as weights. The 4-digit industry ‘Wholesale of solid; liquid and gaseous fuels and related products’ and several as its turnover disproportionate affects our results.

Appendix E: Consumer survey data

Metrics of consumer detriment by market sector

Table E.1 shows estimates for the following metrics, for each of the 44 market sectors covered by the CPS: the percentage of consumers that had bought from the sector in the last 12 months (or bought from it at any time and used the good/service in the last 12 months); the percentage (of those who had used/bought from the sector) who experienced detriment in the last 12 months – ie the incidence of detriment; and the total and median net monetised detriment experienced by consumers for all instances of detriment in the 12-month period.[127]

Table E.1: Incidence of sector use and of detriment experienced, estimated number of UK consumers affected by detriment and net monetised detriment - by market sector, sorted by decreasing incidence of detriment

Sector	*Used/bought from sector in last 12 months (%)*	*Incidence of detriment (%)*	*Unweighted base - for incidence (n)*	*Estimated number of UK consumers affected (million)*	*Total net monetised detriment (£bn)*	*Median net monetised detriment (£)*	*Unweighted base - for net monetised detriment (n)*
Airline	7	36	463	1.3	0.40	28	125
Package holidays and tours	7	35	429	1.2	0.20	42	116
Second-hand vehicles	15	30	1,011	2.4	4.10	463	184
Internet provision	70	29	5,035	10.4	3.40	55	1,025
Electronic devices and software	55	26	3,655	7.4	1.90	33	593
Real estate services	6	26	364	0.7	2.10	142	68
Clothing, footwear and accessories	80	24	5,321	10.0	1.40	9	822
Furniture and appliances	55	21	3,709	6.0	1.80	42	569
Adult care	2	21	140	0.2	*	*	21
New vehicles	6	19	440	0.6	0.60	71	52
Education fees	7	19	369	0.7	2.20	207	43
TV and other digital subscriptions	65	17	4,273	5.7	2.00	38	517
Vehicle maintenance & repair	51	17	3,840	4.6	7.00	118	409
Spectacles and lenses	33	15	2,435	2.5	0.40	42	224
Electricity and gas services	81	15	5,670	6.5	2.20	28	522
Hotels and holiday accommodation	23	14	1,659	1.7	0.50	38	180
Legal and accountancy services	14	14	1,056	1.0	0.80	111	80
Mobile telephone services	82	13	5,539	5.5	1.20	60	418
Public transport and trains	28	13	1,430	1.9	0.40	25	126
Renting services	23	13	1,189	1.6	7.40	442	88
Childcare	6	13	393	0.4	0.40	210	35
Groceries and drinks	93	12	6,182	5.8	0.50	7	426
Entertainment items	49	11	3,034	2.8	0.20	14	182
Removal and storage	6	11	374	0.3	*	*	22
Home and garden maintenance and repair	25	11	2,096	1.5	1.40	109	148
Veterinary	23	11	1,743	1.4	1.20	143	137
Fixed telephone services	51	10	3,976	2.7	0.80	28	277

[127] The survey asked each respondent who said they had experienced detriment about the most recent incident of detriment in at most three market sectors; the results were then scaled-up to make them representative of all the incidents of detriment experienced by study participants in the 12 months. More details are provided in the CPS Report, Appendix B.

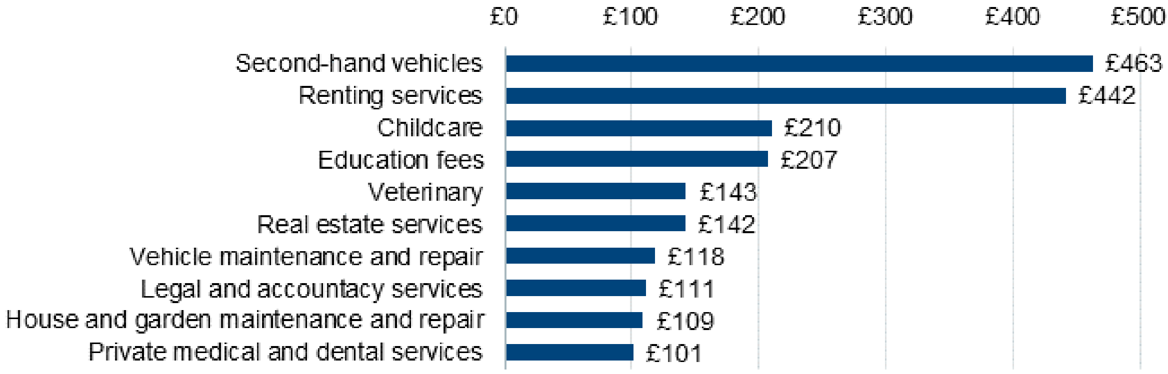
Vehicle rental	5	10	277	0.3	*	*	15
Private medical and dental services	23	10	1,793	1.2	0.60	101	106
Funeral services	4	10	327	0.2	*	*	23
Prescription and non-prescription medicines	40	9	2,526	1.9	0.20	23	134
Fuel and accessories for vehicles	62	9	4,546	2.9	0.70	28	202
Restaurants, cafés and take-away	66	9	4,286	3.1	0.10	5	191
Pet breeder	2	9	149	0.1	*	*	13
Insurance services	57	9	4,218	2.8	1.30	28	229
Sport, cultural and entertainment activities	31	8	2,035	1.3	0.40	28	110
Current accounts, loans and bank services	62	8	4,428	2.7	1.10	28	224
House and garden maintenance products	73	7	5,040	2.8	0.30	14	222
Pension funds and investment services	35	6	2,514	1.1	2.10	55	71
Personal care products	87	5	5,732	2.3	1.20	28	149
Water services	69	5	4,539	1.9	0.20	25	135
Stationery, books, magazines and newspapers	68	4	4,666	1.4	0.10	4	83
Gambling and lottery services	30	4	1,963	0.6	0.00	14	44
Personal care services	43	3	3,153	0.8	0.00	7	56

Source: CPS Report: Table 1 (pages 26-27), Table 3 (page 38) and Table 30 (Appendix E, pages 135-136); and CMA analysis of population estimates provided to the CMA by NatCen (the agency commissioned to conduct the CPS).
Bases: For the column 'Used/bought from sector in last 12 months': All UK adults (18+), unweighted: 6,571 for all sectors. Bases for the other metrics vary by sector and are included as columns in the table.
Notes:
1. The symbol * indicates that the unweighted count is too small for population estimates (n < 30).
2. The CPS findings are from a sample survey and are subject to sampling error. Where the statistics presented are UK population estimates (as is the case for all the columns in the table above, other than those that show the unweighted bases), these are the central estimate for the metric in question. The CPS Report and Appendix E also present the 95% confidence intervals for the estimates of incidence of detriment and total net monetised detriment to provide an indication of their precision. Generally speaking, as noted in Chapter 6, footnote the confidence intervals around the estimates of total net monetised detriment, in particular, are relatively wide, reflecting the high degree of uncertainty associated with these estimates.

Median net monetised detriment by market sector

Figure E.1 below shows the 10 sectors with the highest median net monetised detriment.

Figure E.1 – The 10 sectors with the highest median net monetised detriment



Source: CPS Report, Figure 2, Executive Summary, page 9.

Base: Detriment experiences in the UK in the 12 months to April 2021. Unweighted: Second-hand vehicles 184, Renting services 88, Childcare 35, Education fees 43, Veterinary 137, Real estate services 68, Vehicle maintenance and repair 409, Legal and accountancy services 80, House garden maintenance and repaid 148, Private medical and dental services 106.