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CONTRIBUTED PAPER

Market concentration and productivity: evidence from the UK

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Abstract
We measure product market concentration and business dynamism in the UK from 1997 to 2020 and study the relationship with productivity. Our results show that concentration in the UK is increasing among narrow industries on average, but for a broad market definition, concentration and business dynamism are stable. We find a negative relationship between concentration and productivity for the average firm, but a positive relationship for the average worker. This occurs because higher industry concentration is associated with better allocative efficiency, measured by the proportion of workers in higher-productivity firms.

KEYWORDS
business dynamism, Business Structure Database (BSD), productivity, product market concentration, UK economy

JEL CLASSIFICATION
D2, D4, E2, L1, L4, O4

1 | INTRODUCTION

In many advanced economies, product market concentration is rising. Rising concentration can indicate weaker competition, which can harm productivity, or rising concentration may reflect more efficient firms acquiring market share, which enhances productivity. The aim of our paper is to document product market concentration in the UK, and to examine the relationship between concentration and labour productivity.

The paper makes three contributions. First, we document product market concentration in the UK. We find that concentration for a broad market definition is stable over the sample period 1997–2020, but there was an increase in concentration up to 2016 for a subsample that excludes financial

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services. For a narrower market definition (SIC five-digit), we find that concentration is increasing on average. Secondly, we document business dynamism facts on firm entry and exit levels and measures of allocative efficiency.[1] We find that levels of entry and exit are stable over the period 1997–2020. Allocative efficiency, which captures the extent to which workers are employed at more productive firms, improved until the mid-2010s but has declined since, particularly among industries that have high allocative efficiency. Finally, we analyse the relationship between concentration and labour productivity. We find a negative relationship between product market concentration and labour productivity for the average firm, but a positive relationship for the average worker. The difference occurs because high concentration is positively associated with allocative efficiency, indicating that in concentrated industries, workers are more densely distributed at high-productivity firms.

Beyond the UK policy setting, our paper advances understanding of aggregate concentration behaviour in several ways. First, our data are population-wide across all legal forms. This coverage is more representative of the whole economy than popular proprietary datasets that are biased towards limited liability businesses, which submit full financial accounts.[2] Our data include any business with a tax record, either through value-added tax (VAT) or payroll tax (Pay As You Earn, PAYE). This covers unlimited companies, self-employed individuals, NGOs, and public sector bodies, such as medical surgeries and academy trusts, provided that they have a staff member on payroll or sufficient turnover to register for VAT. This broader inclusion leads to a more accurate measure of concentration as the true market is captured.

A second area that we advance is understanding the effects of market definition on concentration measures. To our knowledge, we are the first to document the sensitivity of concentration measures to market definitions based on SIC industries. We show that in the UK narrow industry definitions of markets have become more concentrated, while broad industry definitions are stable. This is related to Rossi-Hansberg, Sarte and Trachter (2021) who show that the geographical definition of a market is important for understanding concentration. They show that in the US, local markets have become less concentrated, but aggregate markets have become more concentrated.

Lastly, our paper provides new insights into the complex relationship between product market concentration and productivity. At the firm level, we show a negative relationship between concentration and average-firm productivity. At the industry level, we decompose employment-weighted productivity, which represents average-worker productivity, into unweighted productivity, which represents average-firm productivity, and allocative efficiency, which captures the weight of employment in high-productivity firms. We find that while increased concentration decreases average-firm productivity, it increases allocative efficiency. Overall, the positive effect outweighs the negative effect, leading to a positive relationship between concentration and average-worker productivity.

Broadly, this contributes to current debates in the market power literature about whether concentration is 'good' or 'bad' (Covarrubias, Gutiérrez and Philippon, 2020), due to superstar firms or competition abuses. The negative channels are present in our work, but so are the positive channels. Ultimately, when we quantify these effects, we find the positive channel to be stronger. Overall, this supports the superstar firms 'winner-takes-all' hypothesis (Autor et al., 2017), but does not ignore that there are negative effects associated with concentration, potentially due to antitrust abuses (Philippon, 2018).

Theory shows that market concentration and productivity can be positively or negatively related, and this is also reflected in empirical work (Aghion et al., 2005). On the one hand, high concentration can decrease productivity if it reduces competition, raises barriers to entry, or encourages rent-seeking behaviour, such as political lobbying. On the other hand, high concentration can increase productivity through scale economies, network effects, or R&D investment, as in Schumpeterian

[1] Generally, 'business dynamism' refers to a suite of economic indicators. Akcigit and Ates (2021) present ten measures for the US. We focus on those related to concentration, entry and exit, and productivity. There is scope for future research on the UK to analyse employment reallocation, as initiated in Lui et al. (2020), and firm-level growth dispersion.

[2] Bajgar et al. (2020, 2023) assess the advantages and disadvantages of Orbis data.

growth literature. Furthermore, in various models, concentration is ambiguously related to market power and competition. A Cournot model delivers a positive relationship between concentration and market power, as fewer firms raise concentration and increase price setting ability. However, in other frameworks, a decrease in competition increases substitutability due to less differentiation, reduces price–cost margins, and increases concentration (Asplund and Nocke, 2006; Melitz and Ottaviano, 2008). In Schumpeterian growth literature, the profits from market power are required to innovate and improve productivity (Aghion and Howitt, 1992). Review articles by Holmes and Schmitz (2010) and Syverson (2019) provide comprehensive analysis. Our paper emphasises the complexity in the relationship between concentration and productivity, providing evidence on some of the channels through which concentration can be positively or negatively related to productivity.

Recent research finds that product market concentration is rising in the US (Autor et al., 2017; Grullon, Larkin and Michaely, 2019).[3] The evidence for Europe is mixed. Bajgar et al. (2023) show rising concentration in Europe using Multiprod and Orbis data, while Gutiérrez and Philippon (2022) suggest more stable concentration in Europe. The differences occur due to coverage differences in proprietary datasets.

The evidence for the UK is less established, but there is a growing number of policy reports and working papers on the topic. Bell and Tomlinson (2018) analyse UK concentration using Business Structure Database (BSD) data. They find that the market share of the top 100 companies rose from 18 per cent to 23 per cent between 2004 and 2016. Additionally, the weighted-average CR5 across five-digit sectors increased from 39 per cent to 42 per cent, and the weighted-average Hirfindal–Hirschman index (HHI) increased from 880 to 940 units.[4] Aquilante et al. (2019) cover market concentration in a broader study of UK market power (markups) and monetary policy. They conclude that ‘there is no clear trend [in aggregate concentration]’ based on the largest 100 firms from 1998–2016 using Worldscope data on large firms. This is consistent with our finding for broad market definitions, but we show that the conclusion is sensitive to the granularity of the market definition, which helps to reconcile with the Bell and Tomlinson (2018) result. Recent work by Davies (2021) reports a rise in UK concentration and high concentration levels for a subset of four-digit industries in the UK 1997–2018. Cellan-Jones et al. (2022) summarise the findings of Competition and Markets Authority (2022), which reports a growth then decline in CR5 when averaged with revenue weights across four-digit industries. Corfe and Gicheva (2017) focus on consumer industries and find rising concentration. In addition to studying alternative market definitions, and extensive data and methodological background, we also extend the literature by analysing concentration distributions and the relationship to productivity.

To our knowledge, no recent research has examined the relationship between concentration and productivity in the UK, and international studies typically exclude smaller firms. Bighelli et al. (2023) document recent concentration trends in Europe excluding the UK. They find that concentration has risen since 2008 and that it is *positively* related to productivity. This evidence supports the competitive market (‘winner takes all’) hypothesis, where most efficient and innovative producers gain a higher market share (Van Reenen, 2018). The positive correlation is at the sector level, and it is primarily driven by reallocation from less productive to more productive firms. This is similar to our work which shows the positive effect on allocative efficiency offsets the negative effect on unweighted productivity (average-firm productivity). Furthermore, unlike other work, we also provide firm-level regressions which suggest the negative effect on the average firm holds when we control for firm effects, ignoring distributional changes. In other work, Autor et al. (2017) find there is a positive relationship regardless of the productivity measure (output per worker, value-added per worker, TFP, or patents per worker). An important distinction of our work is that we capture smaller firms in our dataset, which can help to

[3] Grullon et al. (2019) use the CRSP–Compustat merged database on publicly listed firms. They also incorporate information on private firms from the US Census Bureau and the US Bureau of Labor Statistics. Autor et al. (2017) use data from the US Economic Census.

[4] They analyse 608 five-digit SIC sectors. They omit sectors in ‘financial services’, ‘wholesale of fuels’ and sectors with high public sector employment.

explain the negative effect of concentration on the average firm, but the positive effect once allocative efficiency is considered.

In Section 2 we discuss our data. In Section 3 we present descriptive statistics on concentration and business dynamism. In Section 4 we analyse the relationship between labour productivity and concentration.

2 | DATA

Our data source is the Business Structure Database (BSD). The BSD is a firm-level dataset provided by the UK Office for National Statistics (ONS) to accredited researchers. It includes basic information on the near population of UK firms, approximately two million per year, and is annual 1997–2020. The data are collected for tax purposes. A firm is on the BSD if it qualifies for value-added tax (turnover exceeds £85,000 in 2022) or has at least one payroll employee.

The advantage of the BSD is that it has near-universal coverage of UK firms across all legal forms, providing they have a record with the tax office. This makes it an ideal dataset for studying concentration, and entry and exit, which require data on the entire market. This differs from studies of concentration, which use proprietary datasets that cover larger, limited liability, firms (e.g. Orbis, Compustat and Worldscope) but are unrepresentative of sole proprietors who make up roughly half of the UK business population. The main variables of interest for us are employment, turnover and industry, and we calculate entry and exit based on activity.

Annual observations in the BSD can correspond to a firm's economic activity for up to the previous two calendar years. This is because the snapshot is taken early in the calendar year and it summarises the most recent accounts the firm has submitted. This explains the presence of the Great Recession with a lag in our descriptive statistics.

2.1 | Full sample and subsample

We present descriptive statistics for a full sample and a subsample of the dataset (see Table 1). The subsample excludes sectors that are known to be poorly measured or in which using turnover to represent output is misleading.

1. The full sample includes all one-digit sectors.
2. The subsample excludes nine one-digit sectors. The following are excluded: financial sector; agriculture; mining; electricity; water; real estate; public administration and defense; education; human health and social work activities.

The subsample contributes half of aggregate sales and a third of employment. The financial sector accounts for the largest turnover in aggregate UK turnover in the BSD followed by the wholesale sector. In the case of employees, education, public administration, and human health represent a significant portion of employment and account for the difference between the full sample and subsample aggregate employees. For our regression analyses and descriptive statistics at a granular industry level, we do not omit sectors because they are controlled for either with fixed effects in regressions or because we are analysing at the industry level.

3 | DESCRIPTIVE STATISTICS

In this section we aggregate the firm-level data and study how the broad trends compare with well-known aggregate trends.

TABLE 1 Full sample and subsample.

Section (SIC07 one-digit)	Number of divisions (SIC07 two-digit)	Full sample	Subsample
Agriculture, Forestry and Fishing	3	Yes	
Mining and Quarrying	5	Yes	
Manufacturing	24	Yes	Yes
Electricity, Gas, Steam and A/C	1	Yes	
Water Supply and Waste Management	4	Yes	
Construction	3	Yes	Yes
Wholesale, Retail and Motor Trade	3	Yes	Yes
Transport and Storage	5	Yes	Yes
Accommodation and Catering	2	Yes	Yes
Information and Communication	6	Yes	Yes
Financial and Insurance Services	3	Yes	
Property (Real Estate Activities)	1	Yes	
Professional, Science and Tech.	7	Yes	Yes
Administrative and Support Services	6	Yes	Yes
Public Administration	1	Yes	
Education	1	Yes	
Human Health and Social Work	3	Yes	
Arts, Entertainment and Recreation	4	Yes	Yes
Other Services	3	Yes	Yes
Household Production	2		
Extraterritorial Activities	1		
Total sections/divisions: 21/88		**19/85**	**10/63**

Note: We always omit Household Production and Extraterritorial Activities.

Figure 1 shows an increasing trend in the number of firms (enterprises) and there are declines during the Great Recession. This growth in the business population is consistent with other proxies of business activity, such as the number of limited-liability companies registered with Companies House (Companies House, 2023), and Business Population Estimates (BPE) from the Department for Business.[5] Neither external data source extends pre-2000, and during this period the growth in firm population is exceptionally strong, potentially reflecting coverage improvements after the dataset was initiated. In our analysis we exclude pre-2000 data, but report these data for our remaining descriptive statistics.

Minor measurement changes increased the coverage of firms in 2008, 2012, 2014 and 2015. In 2008, the ONS added PAYE-only firms. These are firms below the VAT turnover threshold but that have a registered employee. In 2012, 2014 and 2015, tax changes altered the coverage thresholds. These coverage events do not cause obvious breaks in the data.

[5] The Department for Business data can be found at https://www.gov.uk/government/statistics/business-population-estimates-2022/business-population-estimates-for-the-uk-and-regions-2022-statistical-release-html.

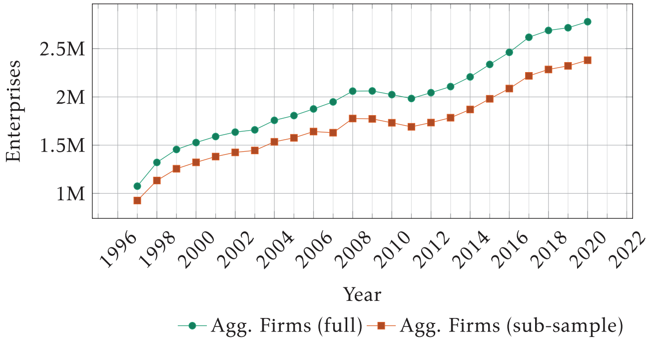

FIGURE 1 Aggregate firms (BSD, 1997–2020). *Source*: Authors' calculations based on BSD 1997–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

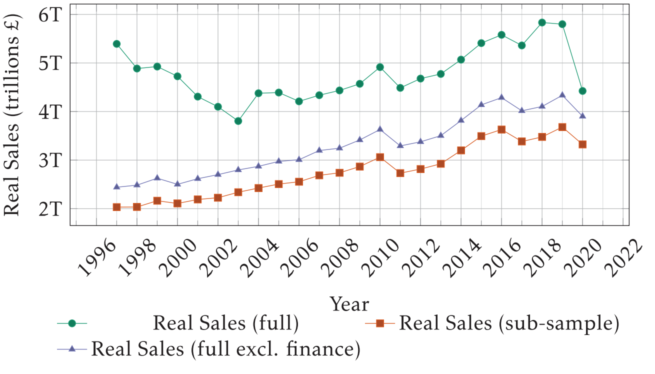

FIGURE 2 Aggregate real sales (BSD, 1997–2020). *Source*: Authors' calculations based on BSD 1997–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

3.1 | Sales, employees and labour productivity

First, we show the underlying components of labour productivity, which is the ratio of sales to employees, and then labour productivity itself. These three plots show that the firm-level data capture the main trends in the aggregate data.

Figure 2 presents aggregate real sales (2016 prices) for the subsample and full sample.[6] Aggregate sales is the sum across all firms in a given year. A puzzling trend in the full sample is high and declining sales between 1997 and 2003, which disappears in the subsample when financial services and other sectors are dropped. This trend causes differences between the full sample and subsample for variables based on sales such as concentration and labour productivity. Because sales is our proxy for output, which is usually measured by GDP or GVA, it should broadly correspond to GDP trends.[7] This seems to be the case. Both samples show an upward trend in aggregate sales over the 2000s with a dip in 2010–2011 that, given the timing considerations of the BSD, corresponds to the recession period of 2008–2009.[8]

[6] Price adjustments for the real series are applied at the two-digit level before aggregation. The price deflators for each two-digit industry are given by the ONS.

[7] Sales are only a proxy for GDP because they include the value of intermediate goods. This creates double-counting that is exacerbated when there are firms with long value-chains. The BSD only includes sales data. There is no information on value-added.

[8] Due to BSD timings, we might expect a lag of up to two years, which means economic activities in 2009 go mostly to 2011 BSD records.

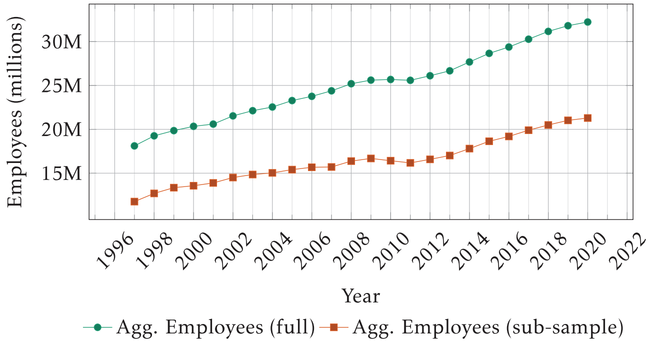

FIGURE 3 Aggregate employees (BSD, 1997–2020). *Source*: Authors' calculations based on BSD 1997–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

As a robustness check we can compare our total turnover figures to total turnover data from the Annual Business Survey (ABS), which is publicly available. The ABS is used in the construction of national accounts. It surveys a representative, random sample of firms, stratified by sector, region and employment size, and then weights these strata to give aggregate figures. The data exclude financial services. We note that ABS analysis (see figure 1 in the source) shows an increase from £3,000 to £3,500 billion in nominal terms between 2008 and 2016.[9] This closely replicates the nominal sales (excluding finance) in our BSD data over the same period. We report nominal sales in Figure D.2 in the online Appendix. An important reason to document this consistency with national accounts data is that alternative approaches to measuring concentration, which use proprietary data such as Orbis, can mismeasure concentration, as explained by Bajgar et al. (2023), and may underestimate productivity dispersion between the median and tenth percentile firm due to under-representation of small firms (Bajgar et al., 2020).

Figure 3 shows aggregate employment data in the BSD. It also reflects documented aggregate trends. Comparing BSD employment data to aggregate UK employment data shows that firms in the BSD cover about 98 per cent of total UK aggregate employment. As at the first quarter of 2018, UK official statistics report employment of 32.36 million, while BSD employment data captured in March 2018 were 31.64 million.[10] The trend in BSD employment is similar to aggregate employment with a lag of one year. Before 2010, aggregate UK employment was at its peak in 2008 while aggregate BSD employment was at its peak in 2009. This shows the firms in the BSD cover a significant portion of UK business activity.

Figure 4 plots aggregate labour productivity according to the BSD data. Labour productivity is calculated as aggregate real turnover divided by aggregate employees in a given year.[11] This is equivalent to measuring firm-level labour productivity (revenue per worker), and calculating the weighted average using the firm's share in aggregate employment as the weight. Throughout the paper, we use real revenue per employee as our measure of productivity. This is consistent with other work that takes a broad macroeconomic approach, such as Bartelsman, Haltiwanger and Scarpetta (2013) and Decker et al. (2016, 2020), due to the comprehensive coverage of revenue and employment data, and strong correlation with value-added per worker measures across industries.

[9] The source of ABS analysis is https://www.ons.gov.uk/businessindustryandtrade/business/businessservices/bulletins/uknonfinancialbusinesseconomyannualbusinesssurvey/uknonfinancialbusinesseconomy2016regionalresults.

[10] The source of the official data is the series 'Number of People in Employment (aged 16 and over, seasonally adjusted):000s' (series ID: MGRZ) https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/timeseries/mgrz/lms, which is from the Labour Market Statistics (LMS) time series.

[11] In the online Appendix, we plot average labour productivity across firms. That is, we calculate firm-level productivity and then take the simple mean across all firms. The trend is similar.

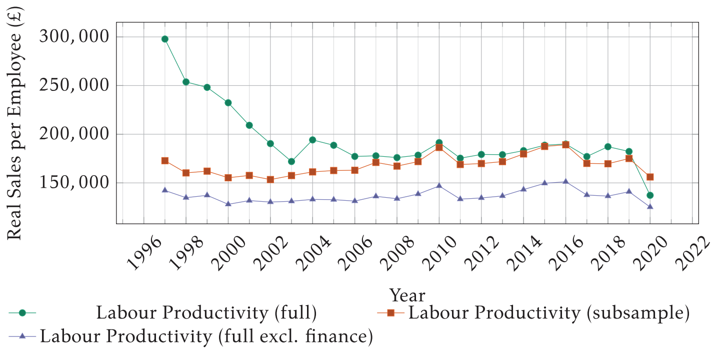

FIGURE 4 Aggregate labour productivity (BSD, 1997–2020). *Source*: Authors' calculations based on BSD 1997–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

Both samples capture a peak in labour productivity in 2010 followed by a stark decline and subsequently low growth. The subsample captures the pre-crisis period better than the full sample, which shows sharply declining productivity from 1997 to 2003.[12] In the subsample, there is steady growth in labour productivity over the 2000s, which declines in tandem with the Great Recession, and follows a slower growth path after 2011.[13] In both samples, the significant increase in labour productivity in 2010 is due to the increase in sales, which was accompanied by a slight fall in the number of employees.

3.2 | Product market concentration

Concentration ratios (CR*N*) represent the sales share of the biggest *N* firms in a market. The market can be the whole economy or granular sectors. In this subsection we report concentration ratios for a broad market definition and more granular five-digit sectors. We also report different definitions in terms of the number of firms included in the numerator of the concentration ratio. Including fewer firms is more likely to capture a dominant group of firms that could engage in anticompetitive behaviour. For example, Cavalleri et al. (2019) and Bajgar et al. (2023) use a variety of CR4, CR8 and CR20 measures, and studies such as Furman and Orszag (2018) use CR50, whilst Aquilante et al. (2019) report CR100.

Figures 5 and 6 report concentration ratios for the aggregate economy, treating the whole economy as the market, similar to evidence in Aquilante et al. (2019). In this context, CR5 represents the sales share of the largest five enterprise units in the dataset. Figure 5 shows that aggregate measures of concentration are stable to decreasing in the UK over the period 1997–2020. There is an increase in concentration from 2009–2010, which typically occurs when firms exit during recession. The CR5 measure fluctuates around the 5 per cent level from 2008 onwards. The implication is that one-twentieth of all sales in the UK go through the largest five firms.[14] Figure 6 shows that, in the subsample, concentration ratios increased up to 2016 but declined rapidly afterwards. CR5 more than doubled (4 per cent to 10 per cent) from 1998 to 2016.[15] The rapid decline in 2020 suggests that the

[12] This early decline in labour productivity is because of the decline in aggregate sales over the same period (Figure 2), whereas employment over the same period (Figure 3) has little effect as it shows a consistent increasing trend. Further, the fall in sales, and thus labour productivity, comes from the finance sector from 1997–2003.

[13] Remember that 2011 in the BSD is capturing economic activity for 2009 and 2010.

[14] In the online Appendix, we plot average CR5 across the main sectors. When we weight each sector by its revenue share, we find similar results.

[15] The spike in concentration in 1997 might be due to under-reporting of smaller firms. If the aggregate economy is missing smaller firms, this reduces total sales and increases the relative size of large firms.

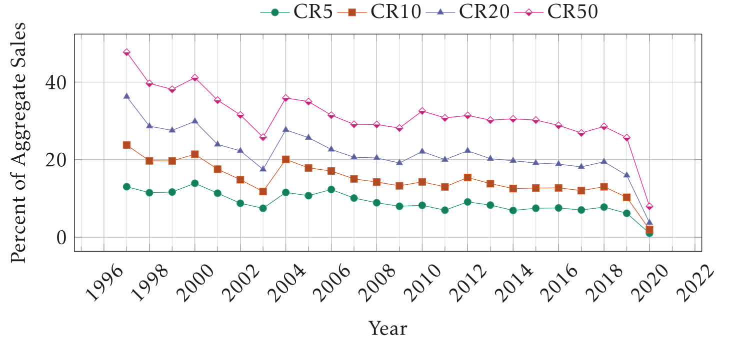

FIGURE 5 Aggregate economy concentration ratios, full sample. *Source*: Authors' calculations based on BSD 1997–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

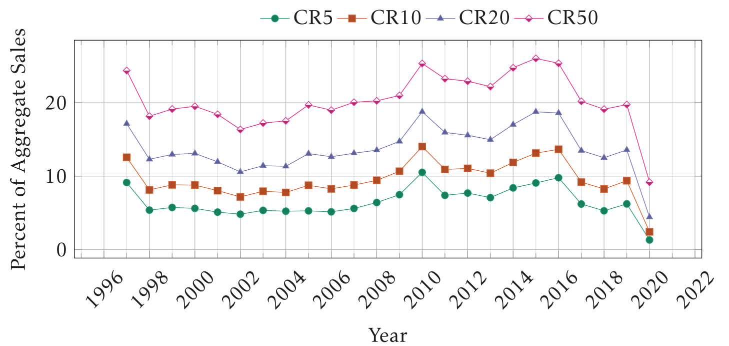

FIGURE 6 Aggregate economy concentration ratios, subsample. *Source*: Authors' calculations based on BSD 1997–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

size of the top-five firms in the economy fell more than proportionally than total market size, likely due to the influence of the COVID-19 pandemic. As a comparison, Cavalleri et al. (2019, see their figures 1 and 2) report similar levels of concentration for several European countries. They report CR4 and use various aggregation techniques.

3.2.1 | Concentration aggregated from five-digit SIC sectors

Figure 7 plots concentration ratios aggregated from the most granular industry definition (five-digit SIC), similar to the preferred definition in Autor et al. (2020) who use four-digit industries. There are approximately 600 five-digit SIC industries each year, depending on whether an industry observes activity or passes disclosure rules within the secure lab. We present the median and mean CR*N* for the concentration level of these industries each year.

We observe an increasing trend across all measures over the period, and this is particularly strong for the median measure. In terms of levels, the mean always exceeds the median, which suggests that there is a tail of high-concentration industries. For CR5, the median five-digit industry has a market share of 15–20 per cent among the top-five firms, and in the average industry the top-five firms have 20–25 per cent of market share. Both measures imply nearly one-fifth of the market held by a small group of firms. The remaining measures, CR10, CR20 and CR50, each increase the amount of market share held, as a wider number of firms is taken into consideration, and the increasing trends become

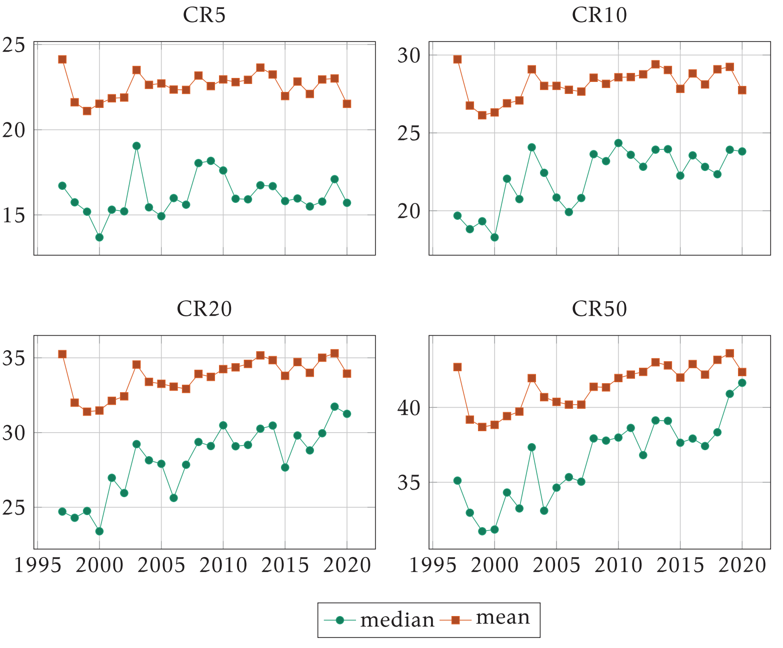

FIGURE 7 Aggregated concentration ratios for full sample from five-digit SIC. *Note*: We calculate concentration at the five-digit SIC, which is approximately 600 industries per year. Then, we take the mean and median across these industries each year. Each panel presents the top 5, 10, 20 or 50 firms. *Source*: Authors' calculations based on BSD 1997–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

starker. For CR10, the amount of market share for the median five-digit industry increases from 20 per cent to 25 per cent over the period considered, and CR20 shows similarly sharp increases.

3.2.2 | Concentration distribution across five-digit SIC sectors

Figure 8 shows the changing distribution of CR5 at the five-digit level. We observe the density of the distribution shifting right over time. This reflects more five-digit industries with higher levels of concentration. This is consistent with the growth in the mean and median concentration that we document in Figure 7.

In Figures 9 and 10, we classify sections of the distribution and plot their evolution over time. Figure 9 shows changes in the percentage of industries that have high and low CR5 from 1997–2020. We classify two parts of the concentration distribution where 'CR5: 0–20%' represents low concentration industries; 'CR5: 80–100%' represents high concentration industries. Over the period, low concentration industries fall from over 20–25 per cent of five-digit industries to under 20 per cent of five-digit industries.

In 2007, there is a discontinuity leading to a spike in high concentration industries. In 2007, SIC industrial classifications were updated from SIC 2003 to SIC 2007. We matched five-digit SIC 2003 classifications with their nearest SIC 2007 classification using ONS methodology. This re-classification is less important for higher degrees of aggregation, such as at the two-digit level where most industries will remain in the same two-digit classification after re-classification, whereas at the five-digit level more industries may cease to exist and be reallocated to other industries.

In antitrust cases, industries are often categorised based on the HHI, which is calculated as the total of squared market shares. The HHI is then used to classify industries as follows: HHI values between 0 and 1,000 indicate low concentration industries, HHI values between 1,000 and 1,800

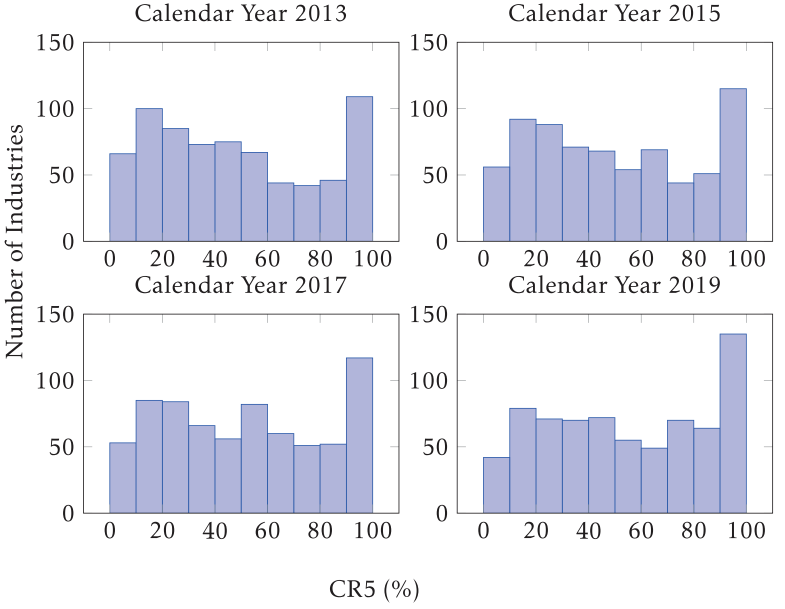

FIGURE 8 CR5 distribution at five-digit level, by year. *Note*: Each histogram shows the distribution of five-digit industries across ten bins of CR5 concentration (0–10, 10–20…90–100 per cent). In all years, there are over 100 five-digit industries with a CR5 of 90–100 per cent. [Colour figure can be viewed at wileyonlinelibrary.com]

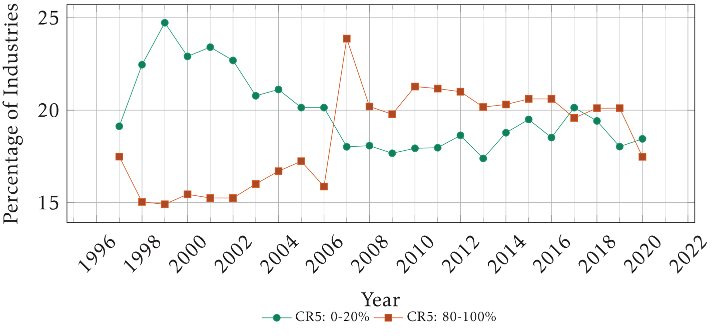

FIGURE 9 Percentage of high and low CR5 industries, 1997–2020, five-digit. [Colour figure can be viewed at wileyonlinelibrary.com]

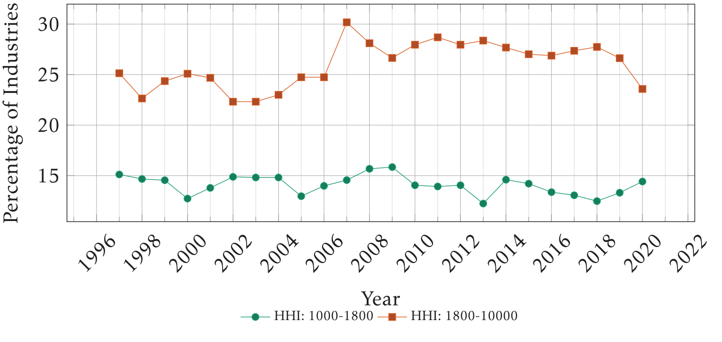

FIGURE 10 Percentage of high and medium HHI industries, 1997–2020, five-digit. [Colour figure can be viewed at wileyonlinelibrary.com]

indicate medium concentration industries, and HHI values between 1,800 and 10,000 indicate high concentration industries (Whish and Bailey, 2021, p. 43).[16] According to this classification, Figure 10 shows that between 25 per cent and 30 per cent of industries are high concentration and this has increased over the sample period. The level of moderately concentrated industries is stable at 15 per cent. The remaining 50–60 per cent of industries are low concentration.

In the online Appendix we provide further analysis of concentration at the BSD sector level.

3.3 | Business dynamism: entry, exit and net entry

Entry statistics are one indicator of 'business dynamism'. Net entry is an alternative indicator of competition, also called 'business churn'. Unlike our other variables, we do not have data for 1997 for entry and exit. We determine entry as the first year that a firm is recorded as being active and records employees and turnover as non-zero or not missing. Exit is the first year the firm is recorded as being inactive having been active the previous year or the first year a firm records turnover and employees as zero.

Figures 11 and 12 show that aggregate entry statistics have a flat trend between 1998 and 2020, suggesting stable business dynamism.[17] The fluctuations we observe are consistent with well-known

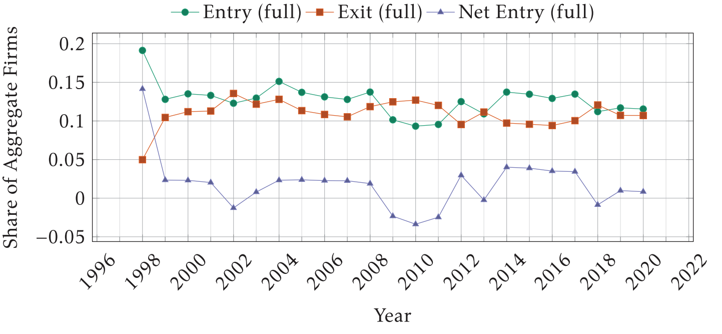

FIGURE 11 Aggregate entry and exit rate for full sample (BSD, 1998–2020). *Source*: Authors' calculations based on BSD 1998–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

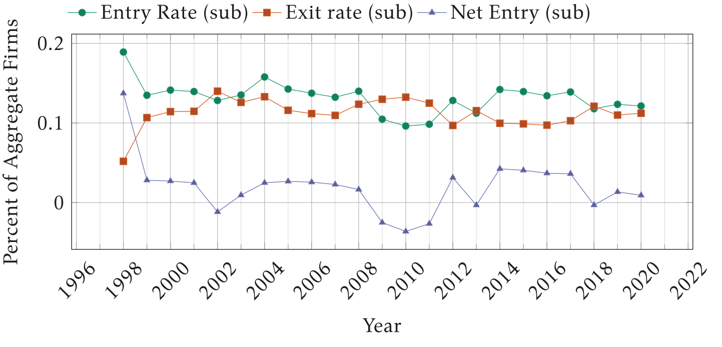

FIGURE 12 Aggregate entry and exit rate for subsample (BSD, 1998–2020). *Source*: Authors' calculations based on BSD 1998–2020. [Colour figure can be viewed at wileyonlinelibrary.com]

[16] Paragraph 16 of the European Commission's *Guidelines on the Assessment of Horizontal Mergers*.

[17] These measures are for entry and exit in the whole economy, not averaging entry and exit statistics across different industries.

characteristics of the business cycle (Tian, 2018). Entry and exit typically co-move, except in recessionary periods when entry declines and exit increases. Additionally, entry is more volatile than exit. Between 2008 and 2011, there was a fall in the number of firms entering and an increase in the number of firms exiting, so net entry became negative. This supports a common mechanism for countercyclical markups in business cycle theory. For example, in business cycle models with Cournot oligopolistic competition such as Savagar (2021), as the stock of firms declines during recession, an individual firm's ability to affect industry output rises, and the price elasticity of demand becomes more inelastic, which raises price setting ability, so price markups rise. This apparent decline in competition during recessions coincides with a higher concentration, as shown in our earlier figures. Figure 12 shows that the entry and exit rates for the subsample are similar. In the online Appendix we provide further analysis of business dynamism at the BSD sector level.

4 | CONCENTRATION AND PRODUCTIVITY

We use reduced-form regression analyses to study the relationship between concentration and productivity. In Section 4.1, we provide firm-level regressions on this relationship, and in Section 4.2, we provide industry-level regressions on industry productivity, and its decompositions. Our aim is to provide controlled correlations on the relationship between productivity and concentration. This approach follows other literature studying concentration in the aggregate (Covarrubias et al., 2020; Bighelli et al., 2023). We lag concentration and net entry measures in order to mitigate reverse-causality, which is the most obvious form of endogeneity. However, this does not overcome the potential for omitted variables, which are correlated with contemporaneous concentration and future productivity, to create endogeneity weakening evidence of causality.

4.1 | Empirical methodology

The dependent variable is labour productivity and the main independent variable is concentration. We also include net entry as an alternative indicator of competition. Our regression specification is

$$\begin{aligned}\text{Productivity}_{\imath\jmath t} &= \alpha_\jmath + \alpha_t + \beta_1 \text{Concentration}_{\jmath t-1} + \beta_2 \text{Net Entry}_{\jmath t-1} \\ &\quad + \beta_3 (\text{Concentration}_{\jmath t-1} \times \text{Net Entry}_{\jmath t-1}) + \gamma^\intercal \boldsymbol{x}_{\imath\jmath t} + \varepsilon_{\imath\jmath t}. \qquad (1)\end{aligned}$$

The subscript $\jmath$ indicates a sector and $\imath$ indicates a firm. We consider two-digit SIC sectors. There are 85 two-digit sectors. Concentration and net entry are sector-level variables, whereas $\boldsymbol{x}$ is a vector of firm-level control variables to account for other factors that may influence productivity. The firm-level controls are market share, firm size and firm age. The dependent variable, productivity, is also at the firm level. We use industry ($\alpha_\jmath$) and year (α_t) fixed effects.

We use a two-digit definition in our regression analyses for several reasons. First, it appears to capture distinct industry functions well (e.g. veterinary or postal activities).[18] At a higher level there is little distinction between industry activities, whereas if we go more granular it becomes more likely that some firms will operate across multiple industries, but their activity will only be recorded in their primary industry. Second, at the two-digit level few firms change SIC definitions from pre-2007 SIC classification to post-2007 SIC classifications. Lastly, we are consistent with comparable studies such as Furman and Orszag (2018) for the US and Cavalleri et al. (2019), Bighelli et al. (2023) and Bajgar et al. (2023) for Europe.

Table 2 reports the measure that we use for each variable in equation (1). Our main measure of concentration is CR5. We use CR5, rather than CR10, CR20, CR50 or HHI, because a lower number

[18] We provide a list of two-digit industries in the online Appendix.

TABLE 2 Variables and corresponding measure in the data.

Variable	Measure	Unit
Productivity	$\log\left(\frac{\text{Real Sales}_{yt}}{\text{Employees}_{yt}}\right)$	Log
Concentration	$\text{CR5}_{jt-1} = \frac{\sum_{i=1}^{5}\text{Real Sales}_{yt-1}}{\text{Real Sales}_{jt-1}} \times 100$	% of market
Net entry	$\frac{\text{Births}_{jt-1}-\text{Deaths}_{jt-1}}{\text{Firms}_{jt-1}} \times 100$	% of active firms
Market share	$\frac{\text{Real Sales}_{yt}}{\text{Real Sales}_{jt}} \times 100$	% of market
Age	$\text{Birth Date}_y - \text{Death Date}_y$	Years
Size	$\log\left(\text{Employees}_{yt}\right)$	Log

of firms better captures weak competition. That is, it is easier to sustain anticompetitive practice with high market share among fewer firms.[19]

4.1.1 | Estimation strategy

We use first-difference estimation to estimate regression (1).[20] First-difference estimation accounts for unobservable firm-specific effects. We use first-differences instead of fixed effects due to computational restrictions in the secure lab. We account for within-cluster error correlation by clustering standard errors at the sector level. A disadvantage of using both first-difference estimation and lagged independent variables is that we lose at least two observations per firm in the regression analysis. This accounts for the difference in observations recorded in the summary statistics table and regression tables.

Productivity and concentration are subject to reverse-causality. Increased concentration causes productivity to decrease if it causes anticompetitive behaviour. However, increased productivity causes increased concentration if productive firms increase their market share. The former relationship implies a negative causal relationship from increased concentration to decreased productivity, whereas the latter relationship implies a positive causal relationship from increased productivity to increased market power. To mitigate the effect of this form of endogeneity, we use a lagged measure of concentration.

We include 'net entry' as an alternative indicator of competition in an industry. Net entry should keep incumbent firms operating efficiently. Therefore, we would expect it to have a positive coefficient. Similarly to concentration, net entry also suffers from the reverse-causality problem. That is, net entry might increase productivity because it keeps incumbent firms operating efficiently. However, high-productivity industries may encourage more entry.[21] Both directions of causality imply a positive relationship. Similarly to concentration, we mitigate the reverse-causality between labour productivity and net entry by using lagged measures of net entry.

We include a 'concentration × net entry' interaction term. We expect that when net entry is high, then an industry does not face weak competition. Therefore, the effect of concentration on productivity will be less negative when net entry is high and could be positive if the presence of concentration occurs when there is high net entry as concentration is increasing due to high-productivity firms

[19] In the online Appendix, we perform a sensitivity analysis of our results to alternative measures of concentration.

[20] In the online Appendix we provide pooled OLS estimates.

[21] This could be because of a new technology. If technological innovations are industry-specific, this is controlled for by the fixed effects. The problem would be more prominent with an aggregate industry-wide technology improvement.

TABLE 3 Summary statistics.

Variables	Number of observations	Mean	Median
Productivity	40,610,710	75,360	77,650
CR5 (%)	41,313,405	16.95	14.05
Net entry (%)	41,313,405	1.78	1.14
Market share (%)	41,313,405	0.00	0.00
Firm age	41,313,405	10.39	7
Employees	41,313,405	12.72	2

out-competing entrants. Conversely, if net entry is low, this implies little competition so the effect of concentration should be more negative.[22] In other words, we use net entry as an indicator of whether concentration is taking place for 'good' (productive frontier) or 'bad' (anticompetitive behaviour) reasons.

4.1.2 | Regression variable summary statistics

Table 3 presents summary statistics of variables used in the regression. CR5, net entry and market share are percentage of two-digit industry. Productivity, age and employees are firm level. The average labour productivity is £75,000, which implies a worker generates £75,000 sales for a firm in a year. This figure appears high and might be inflated because the dataset excludes firms that do not pay VAT (revenue below £85,000 in 2018) and have no employees.[23] For context, average real income over the period 2000–2018 is roughly £28,000 (2020 prices). This implies a 37 per cent average share of wages in sales. CR5 shows average concentration ratios across two-digit industries. On average, the top-five firms account for 17 per cent of turnover. Average net entry at a two-digit industry is 1.8 per cent of total firms in the industry, which implies a net increase in firms each year. Market share shows that on average firms are very small. An average firm accounts for 0.004 per cent of sales in its two-digit industry. Median firm age is 7 years while the median number of employees (firm size) is 2. The difference between mean and median for firm size implies there is a large number of small firms (positive skew).

4.1.3 | Firm-level regression results

The results of our regression are given in Table 4.[24]

The results in Table 4 show a statistically significant negative relationship between concentration and labour productivity in columns 1–3. Higher concentration levels are associated with lower labour productivity levels. The results in the full specification have the following economic interpretations: a 1 percentage point increase in CR5 decreases productivity by 0.07 per cent; a 1 percentage point increase in net entry increases productivity by 0.04 per cent; a 1 percentage point increase in market share increases productivity by 19.2 per cent; an increase in firm age by one year increases productivity

[22] This interpretation focuses on the effect of concentration, given net entry behaviour. However, there are two interpretations of an interaction term: the relationship between productivity and net entry depends on concentration or the relationship between productivity and concentration depends on net entry. The alternative interpretation is that the effect of net entry will vary depending on the level of concentration. When concentration is high, net entry should have a stronger positive effect on productivity.

[23] Firms with sales below the VAT threshold are included if they have a PAYE employee.

[24] In the online Appendix, we provide results for pooled OLS regressions. These do not control for firm fixed effects. The results have a similar economic significance but are less statistically significant. The interpretation of the pooled-OLS and FD regression coefficients is identical.

TABLE 4 Effect of CR5 on log labour productivity.

	All	All	All	All	All	Serv.	Prod.
$\Delta CR5_{t-1}$	-0.082^{***}	-0.069^{**}	-0.068^{**}	-0.069^{**}	-0.067^{**}	-0.073^{**}	0.005
	(0.002)	(0.027)	(0.027)	(0.028)	(0.027)	(0.037)	(0.035)
Δnet entry$_{t-1}$			0.053	0.033	0.042	0.092	−0.079
			(0.058)	(0.073)	(0.068)	(0.087)	(0.071)
$\Delta(CR5_{t-1}$				0.128	0.097	0.024	0.029
$\times$Net Entry$_{t-1})$				(0.204)	(0.182)	(0.249)	(0.158)
Δmarket share$_t$					0.192^{***}	0.298^{***}	0.110^{***}
					(0.032)	(0.044)	(0.028)
Δfirm age$_t$					0.007^{**}	−0.001	0.005
					(0.003)	(0.004)	(0.003)
Δfirm age$_t^2$					-0.018^{**}	−0.001	−0.012
					(0.008)	(0.011)	(0.007)
$\Delta \ln(\text{firm size}_t)$					-0.564^{***}	-0.510^{***}	-0.621^{***}
					(0.038)	(0.022)	(0.056)
$\Delta \ln(\text{firm size}_t)^2$					−0.021	−0.529	0.853
					(0.538)	(0.777)	(0.992)
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
N	31,914,138	31,914,138	31,914,138	31,914,138	31,914,138	16,190,002	3,392,781
R^2	0.000	0.003	0.003	0.003	0.106	0.084	0.146
Clusters		85	85	85	85	39	37

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Regressions are in first difference. Dependent variable is log labour productivity. All independent variables are in levels, except firm size which is in logs. CR5, net entry and market share are measured at two-digit SIC industry level. Coefficients and standard deviations for the quadratic terms are multiplied by 100 (i.e. variable unit is divided by 100.) CR5 and net entry variable units are shares not percentages. Standard errors are clustered at two-digit industry level. Sales are constant 2016 values. Industry fixed effects are at the two-digit sector level. *Source*: BSD data, 2000–20.

by 0.01 per cent, but at a decreasing rate; an increase in firm size of 1 per cent (employees) decreases productivity by 0.56 per cent.

In terms of economic significance, our relationship suggests a 10 percentage point increase in CR5 corresponds to a 0.7 per cent fall in productivity levels of the average firm. Because average labour productivity is approximately £80,000 sales per worker per year, a 5 percentage point increase in CR5 corresponds to a £280 decrease in sales per worker per year.

Our firm-level results are supportive of hypotheses that concentration relates negatively to productivity, potentially due to lower competition or antitrust abuses, and are consistent with papers such as Covarrubias et al. (2020) and De Loecker, Eeckhout and Unger (2020). It is important to note that our firm-level results are for the average firm, conditional on the factors we control for, but do not consider the distributional implications of concentration reallocating resources across producers.

4.1.4 | Specific sector regressions: services and production

The final two columns of Table 4 report the relationship between concentration and productivity by sector. We analyse the two largest BSD sectors 'Production' and 'Services'.[25] The results show

[25] These are ONS-specific aggregations of two-digit sectors called 'BSD sectors'. They are used in the BSD and other business datasets because they correspond to sampling frames used in business surveys. 'Services' is called 'Other Services' by the ONS definition (see the online

opposite effects of concentration on labour productivity across the two sectors. In services, there is a negative and significant effect of concentration on productivity, whereas there is a positive but not significant effect in the production sector. Notably, the sample size falls sharply in these subsets, which will limit the precision of results.

In services, the result appears the same as for our full specification. The relationship and magnitude are similar, indicating that the average firm has weaker productivity when there is greater concentration. It is common in UK analyses for services to reflect the aggregate outcomes due to the size of the sector. We observe that this subsample represents over half of firms. The sector is also characterised by a large number of smaller (low-employee) producers, which can help to rationalise why greater concentration may negatively relate to productivity of the average firm. For example, if higher concentration leads larger services firms to acquire the more productive workers, then the average firm will have lower productivity. This is why industry-wide measures of productivity are important, which motivates our next section, because at the firm level we overlook distributional effects that could counteract the average firms' experience.

Although the result for production is insignificant, there are plausible economic mechanisms that could explain the lack of a negative relationship and indicators of a positive relationship. Concentration may be positively related to productivity in the production sector due to economies of scale. If production requires a large overhead cost, then distribution of economic activity across small firms will under-utilise the overhead and damage productivity. Hence, greater concentration increases utilisation, which increases productivity. In the production sector, net entry has a negative relationship with productivity. This also supports a theory that entry leads to replication of fixed overhead costs that are under-utilised and weaken productivity. In the production sector, the interaction term indicates a negative relationship between concentration and productivity that is worse when net entry is high. Hence, greater concentration increases the negative effect of entry.

4.2 | Productivity decomposition

Our firm-level regression results show that a higher concentration is associated with lower productivity for the mean firm with the characteristics for which we control. However, this firm-level approach does not capture the distribution of employment across firms. To understand the effect on average-worker productivity, we study the relationship between concentration and the weighted-average productivity in an industry.

4.2.1 | Decomposition methodology

In general, we can express a weighted average as an additive decomposition of the unweighted average and a dispersion term:[26]

$$x_j \equiv \sum_{i=1}^{N} \omega_i x_i = \bar{x}_N + \sum_{i=1}^{N} (x_i - \bar{x}_N)(\omega_i - \bar{\omega}_N). \tag{2}$$

Appendix). These two sectors are the sectors comprising most two-digit industries. In addition, they are the largest sectors, in both aggregate turnover and employment terms. Services accounts for 50 per cent of total turnover and production 15 per cent.

[26] This general decomposition applied to productivity is referred to as a static OP decomposition (Olley and Pakes, 1996). Bighelli et al. (2023) use the decomposition to understand business dynamism and concentration. Their analysis focuses on the relationship between concentration and allocative efficiency, which is one component of the decomposition, whereas we analyse the relationship with all components of the decomposition, and we show that the unweighted results are consistent with our firm-level results in the previous section. Furthermore, this highlights both the positive and negative potential of concentration for productivity. We are able to do this extension because we have firm-level data, rather than the 'micro-aggregated' data in their cross-country panel.

This provides a cross-sectional decomposition at a point in time, and x_j represent industry j weight-average productivity. To improve clarity, we omit the time t and industry j subscripts in equation (2) as the decomposition is applied to an industry in a given time period. We apply the decomposition to approximately 85 two-digit SIC industries each year 2005–20. There are N firms in an industry and each firm is indexed by $i \in 1 \dots N$. The variable $x_i = sales_i / L_i$ is a firm's labour revenue productivity, and $\bar{x}_N = (1/N)\sum_{i=1}^{N} x_i$ is the unweighted average of labour productivity. The weight $\omega_i \equiv L_i / \sum_{i=1}^{N} L_i$ is a firm's labour share in total industry labour.[27] And, because shares sum to one, then the unweighted-average share is $\bar{\omega}_N = (1/N)\sum_{i=1}^{N} \omega_i = (1/N)$.

The weighted average on the left-hand side is the average-worker productivity, and the unweighted-average productivity is the average-firm productivity. The cross-product of deviations term measures the covariation of firm productivity and the employment share. A common economic interpretation is allocative efficiency (Olley and Pakes, 1996). It captures the extent to which workers are allocated to high-productivity or low-productivity firms. It is positive when above-average productivity firms have above-average employment, or vice versa. It is negative when below-average productivity firms have above-average employment, or vice versa.

In our case, we can write

$$\sum_{i=1}^{N} (x_i - \bar{x}_N)(\omega_i - \bar{\omega}_N) = \frac{sales_j}{L_j} - \frac{1}{N_j} \sum_{i=1}^{N_j} \left(\frac{sales_i}{L_i} \right).$$

In other words, allocative efficiency is the difference between average-worker productivity and average-firm productivity:

$$\text{allocative efficiency} = \text{average-worker productivity} - \text{average-firm productivity}.$$

Our application to labour (revenue) productivity, weighted by the labour share is the same as Bartelsman et al. (2013) for the US, and Bighelli et al. (2023) for Europe. An advantage of our work with UK data is that we have representation across firm size and legal forms. We are not restricted to larger firms or micro-aggregated data.

For the descriptive figures that follow, we drop industries 06 (oil), 07 (mining metal), 09 (quarrying), 12 (tobacco), 19 (petrol manufacturing), 35 (electricity), 39 (waste), 46 (wholesale), 64 (finance), 65 (insurance), 66 (other finance), and we restrict the time period to 2005–20. This removes outliers, which improves plot scaling. In our regression analyses, we do not omit industries, as we control for fixed differences between industries. Whether we include or exclude this list of industries does not affect the signs or significance of the results. In fact, the significance increases if these industries are removed.

4.2.2 | Decomposition descriptive statistics

The plots in Figure 13 show average-worker productivity against average-firm productivity for a selection of four years. In each plot, a scatter point represents a two-digit industry. The $y = x$ line captures the case when the two measures coincide, which implies the allocation term is zero. Points above the line are industries where there is positive allocative efficiency, so above (below) average

[27] As our measure of productivity is labour revenue productivity ($x_i = sales_i / L_i$), the weighted average is equivalent to total sales divided by total employment:

$$\sum_{i=1}^{N} \omega_i x_i = \sum_{i=1}^{N} \left(\frac{sales_i}{L_i} \times \frac{L_i}{\sum_{i=1}^{N} L_i} \right) = \frac{\sum_{i=1}^{N} sales_i}{\sum_{i=1}^{N} L_i} = \frac{sales_j}{L_j}.$$

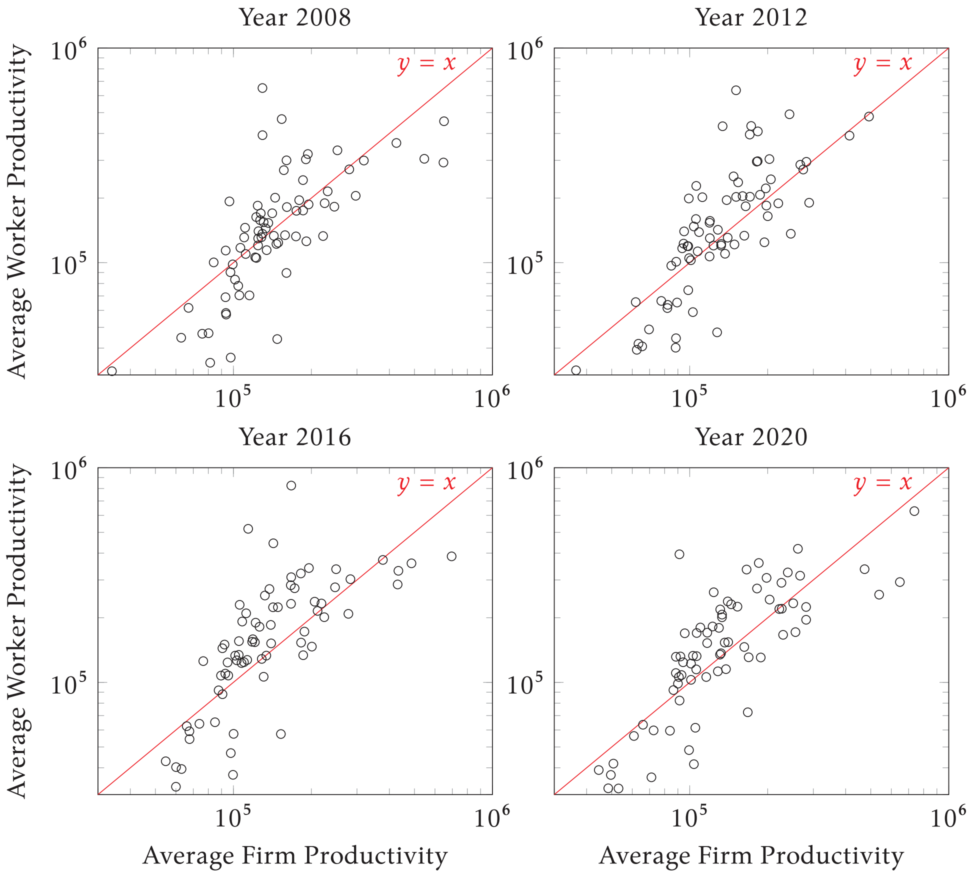

FIGURE 13 Average-firm productivity versus average-employee productivity. *Note*: The axes use logarithmic scaling. The domain is 30,000 to 1,000,000 for both axes in each plot. Each point is a two-digit sector. The $y = x$ line demarcates between positive and negative allocative efficiency. Above the line there is positive allocative efficiency, which implies that average-worker productivity exceeds average-firm productivity, and vice versa below the line. [Colour figure can be viewed at wileyonlinelibrary.com]

productivity firms have above (below) average employment, whereas points below the line represent industries where allocative efficiency is negative, so above (below) average size firms have below (above) average productivity. Figure 13 illustrates that most variation in our firm–year panel data occurs between industries, while variation over time is limited.

In Figure 14 we illustrate the cross-sectional variation in allocative efficiency across industries in 2015, which we take as a representative year. Industries 01–49 mostly have positive allocative efficiency, whilst industries 50–96 mostly have negative allocative efficiency. This division roughly represents production industries in the first half, such as agriculture, mining, manufacturing and utilities. The second half is services such as real estate, professional & scientific, education, health and arts. In the online Appendix, we present this break-down in terms of average-firm and average-worker productivity, rather than the allocative efficiency, which is the difference between the two. We also include a key to identify the industries from their two-digit code.

In Figure 15 we present the time-series variation in the data through the mean and quantiles across industries each year. Allocative efficiency broadly increased over the sample period, but has declined since 2016. On average, allocative efficiency is positive, implying that average-labour productivity exceeds average-firm productivity.

From our descriptive analysis of allocative efficiency, we conclude that the bulk of industries have positive allocative efficiency. The more productive firms employ more labour. Allocative efficiency is

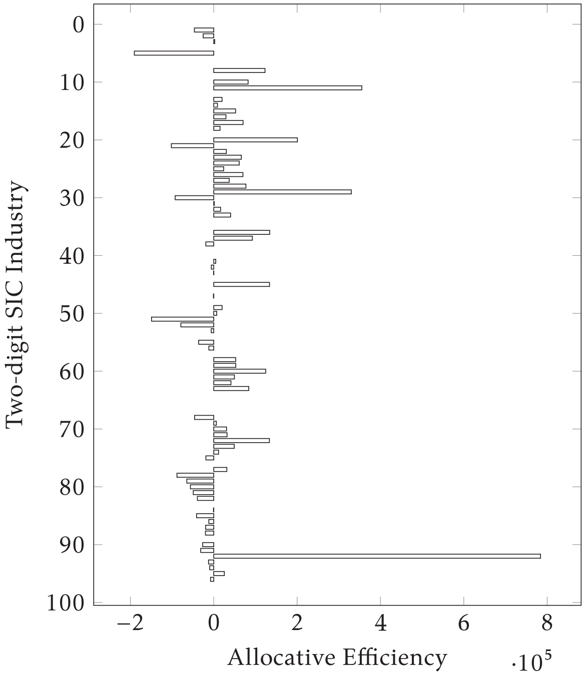

FIGURE 14 Allocative efficiency by industry in 2015. *Note*: In online Appendix F.2, we provide a key for the SIC codes.

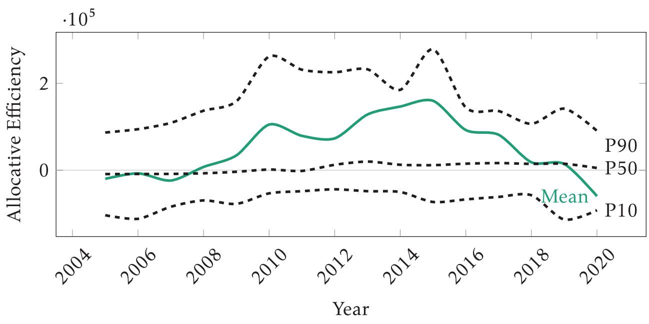

FIGURE 15 Allocative efficiency over time, percentiles over industries. [Colour figure can be viewed at wileyonlinelibrary.com]

more common in production industries, whereas in services below-average productivity firms tend to have above-average employment. Over time, allocative efficiency has improved, but it has flattened or declined since 2016.

4.2.3 | Decomposition regression

We estimate the impact of lagged concentration (CR5) on each component of the decomposition, controlling for industry fixed effects (α_j) and time fixed effects (α_t):

$$y_{j,t} = \alpha_j + \alpha_t + \beta_1 \text{Concentration}_{j,t-1} + v_{j,t}. \tag{3}$$

TABLE 5 Effect of CR5 on decomposition components, OLS.

	ln(worker productivity)	ln(firm productivity)	Allocative efficiency
$CR5_{t-1}$	0.54***	−0.10	507,735**
	(0.08)	(0.10)	(189,981)
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
$N \times T$	1,250	1,250	1,250
N	85	85	85

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. CR5 is measured at two-digit SIC industry level. Industry fixed effects are at the two-digit sector level. *Source*: BSD 2005–20.

Here, y is the outcome of interest, namely the logarithm of weighted productivity (average-worker productivity), the logarithm of unweighted productivity (average-firm productivity) and the dispersion term (allocative efficiency), not logged due to negatives. The subscript j indicates a two-digit sector, while t is time in years.

The economic implications of the findings presented in Table 5 can be summarised as follows. An increase of 1 percentage points in CR5 relates to an increase in average-worker productivity of 0.5 per cent. However, it results in a decrease in average firm productivity of 0.1 per cent, although this decrease has limited statistical significance; it is still one standard deviation from zero. Furthermore, this increase in CR5 relates to better allocative efficiency, specifically an increase of £5,077.[28] The magnitude is approximately half of the average allocative efficiency over the full, pooled, sample. The results in Table 5 for the average-firm effect (−0.1 per cent) are consistent with our firm-level findings in Table 4 (−0.07 per cent), which additionally controlled for firm fixed effects.

We conclude that higher concentration is associated with lower productivity for the average firm. But it is associated with a greater weight of employees in higher productivity firms, so average-worker productivity is higher in more concentrated industries. Therefore, concentration is associated with greater allocative efficiency supporting the ‘winner takes all’ hypothesis of efficient workers acquiring market share (Van Reenen, 2018; Autor et al., 2020).

Our empirical results reflect the nuanced theoretical relationship between productivity and concentration. Based on existing work, a plausible interpretation of our results is that in more concentrated industries, a dominant group of firms may benefit from scale effects, which benefits the disproportionate share of workers that they employ, raising average-worker productivity. But despite higher average-worker productivity, average-firm productivity suffers, potentially because the average-firm faces anti-competitive behavior, or it cannot operate at a ‘minimum efficient scale’ to exploit scale economies.[29] This interpretation is consistent with existing evidence that highly efficient ‘superstar’ firms have driven market concentration (Autor et al., 2020), and their dominance is closely related to intangible investment (Crouzet and Eberly, 2019; Bessen, 2020; Bajgar, Criscuolo and Timmis, 2021), but regulation has also weakened (Gutiérrez and Philippon, 2017; Grullon et al., 2019), which could harm the average firm.[30] Furthermore, Lashkari, Bauer and Boussard (2024) link intangible

[28] We are interested in a 1/100 of a unit increase which cancels-out when interpreting the logarithmic changes in percentages $100 \times \beta_1 \times \Delta CR5$ where the change in CR5 is 1 percentage point $\Delta CR5 = 0.01$. For allocative efficiency, which is in levels, we have a 1/100-unit change $\Delta CR5 = 0.01$ in the absolute value of the coefficient $\beta_1 \times \Delta CR5$.

[29] An interesting exercise for future work is to study how different quantiles of the firm size distribution respond to industry concentration. This would provide richer evidence on why the average-firm effect and firm-level effect are negative. It could also enrich the evidence of mechanisms. For example, if the subset of large firms' unweighted-average (or firm-level) productivity declines as concentration increases, this could indicate lack of competition.

[30] Aghion et al. (2023) and De Ridder (2024) propose theories linking intangible investment to growing market power. Corrado et al. (2022) review literature on intangible investment.

investment with scale economies, and Kariel and Savagar (2023) show that scale economies have increased in the UK.

5 CONCLUSION

We document product market concentration and entry dynamics in the UK using an administrative dataset of all firms from 1997–2020. The dataset includes comprehensive coverage of firm size, legal form and sectors. We show that the market share of the largest firms in the economy is stable over the period. However, the largest firms' market share increases for most of the period when finance is excluded, and for narrow industry definitions (five-digit SIC) we find that average concentration is rising. We show that trends in entry and exit are relatively stable over the period, differing from a well-documented decline in the USA.

Using measures of market concentration at the two-digit industry level, we find evidence that product market concentration and firm productivity are negatively related for the average firm. However, when we consider weighted-average productivity at the industry level, we find this result is overturned. This reflects that weighted-average measures include distributional effects. Our results at the industry level show that although concentration remains negatively related to the average-firm productivity, it is positively related to the average-worker productivity. This arises because in industries with more concentration, workers locate at more productive firms. In other words, concentration is positively associated with allocative efficiency, and we confirm this relationship directly.

Future work should investigate more sophisticated measures of market power and productivity. For example, Hwang, Savagar and Kariel (2023) investigate the relationship between price markups and TFP in the UK. Nonetheless, it is a useful measurement exercise to document concentration trends in the UK, their sensitivity to market definition, and the nuanced relationship with productivity, particularly given the current prevalence of concentration studies in policy, the media, and for many other countries.

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We provide a web app to analyse our data further https://asavagar.shinyapps.io/UK-market-structure/.

DISCLAIMER

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.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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