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## ABSTRACT

When labour market competition is imperfect, positive industry (and firm) productivity shocks can be passed through to workers in the form of higher wages. We document how the UK auto industry, following a period of decline, experienced a four-decade-long productivity boom. There was a thirteen-fold increase in real output per worker between 1980 and 2018, compared to a four-fold increase in manufacturing. Greater foreign ownership, tougher competition and improved industrial relations all likely played a role. The greater use of intermediate inputs (outsourcing) and growing capital intensity account for most of this growth, but we estimate that TFP still grew three times as fast in the auto industry than the rest of manufacturing. Examining whether this productivity increase has been shared with employees, we find that auto workers experienced far stronger hourly wage growth than workers in the rest of manufacturing. After controlling for individual fixed effects, the auto wage premium relative to the rest of manufacturing doubled from 8% in the 1980s to 17% in the 2010s. Interpreted through the lens of a rent sharing model, we estimate that most of the wage increase (63% in the baseline case) can be accounted for by the auto productivity boom. In contrast, the bargaining power of UK auto workers seems to have fallen. If worker power had held up at the 1980s level, the wage premium would have been about 38% higher in the 2010s.

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# 1 Introduction

In the competitive model of a labour market, an individual worker benefits from Hicks Neutral productivity increases in their industry indirectly through falls in output prices. In contrast, imperfectly competitive models of wage determination suggest positive productivity shocks can also benefit workers directly through various forms of "rent sharing" (Manning 2011). A large and growing body of empirical work suggests these rent sharing effects are non-trivial (see the survey in Card et al. 2018 and contributions by Kline et al. 2019; Van Reenen 1996).[1]

With a few notable exceptions (e.g. Kroft et al. 2020; Rose 1987), these papers tend to examine rent sharing across a large number of industries. We contribute to this literature by examining the presence and magnitude of such direct benefits in the context of the industry-specific productivity boom experienced by the UK auto manufacturing sector between 1980 and 2018.[2]

There is a long tradition of car-building in Britain. Rover (now part of Jaguar Land Rover, JLR) was founded in 1878 and Rolls Royce in 1906. In 1955, the UK produced 1.2 million cars and was the world's second largest auto manufacturer after the US. Decline set in, however, and the industry became a byword for inefficiency, industrial strife and poor quality. In 1968, the government engineered the creation of British Leyland, an ill-fated "national champion" which was the merger of many separate manufacturers and ultimately BMC and Leyland Motors. Poor integration, weak management and industrial disputes continued. Despite (or because of) large government subsidies, however, the industry's problems deepened in the 1970s, there was industrial turmoil (ten times as many days were lost to strikes in the UK than in Germany), with weak management and falling sales. The election of Mrs. Thatcher in 1979 prompted a cutback of public support, new management and a large reduction of the workforce.

Since then there has been quite a turnaround. We document that the auto industry grew from just over 5% of manufacturing output in 1980 to over 11% in 2018. By then, 168,000 people were employed directly in the industry and around 823,000 in the supply chain. Output per worker rose by a factor of 12 over the period 1980-2018 compared to a factor of 4 in manufacturing as a whole and 2 in the market economy.[3] We show that much of this was due to the growth of global value chains (intermediate input intensity), increases in capital intensity and also a substantial growth in efficiency (TFP). Although the car industry also enjoyed relatively fast productivity growth in other countries, the UK stands out for its impressive reversal of fortunes.

We do not delve in depth into the fundamental causes of this increased productivity, which has been the focus of a large literature. One important aspect has been the growth of foreign ownership (see Griffith 1999, for example). The Thatcher government encouraged foreign multinationals to locate in the UK. In 1986, the Japanese car firm

1. Other recent contributions include Berger et al. (2022).

2. We use the American "auto" and the British "car" interchangeably in this paper.

3. The market economy is the non-financial private sector of the economy, i.e. dropping government entities, health, education as well as finance, insurance and real estate.

Nissan entered Europe for the first time, building a manufacturing plant in Sunderland, which (at the time of writing) remains the most productive factory in Europe. The firm sought to engender the same commitment to quality, flexibility and teamwork as it had in its Japanese workforce with a single union agreement and binding arbitration, massively reducing industrial disputes. Similar strategies were sought in the Toyota's plant near Derby and Honda's plant in Swindon. In 1994, the last of the large volume British owned car manufacturers, Rover, was sold to Germany's BMW. [4] The growth of foreign ownership helped improve productivity directly, as foreign multinationals tend to be higher productivity (because of technological and managerial know-how - see Bloom et al. 2012) and indirectly through learning spillovers and higher competitive pressure (e.g. Alfaro and Chor 2023; Amiti et al. 2023).

In addition to FDI, being part of the European Single Market fostered stronger competition and opened new export markets (Owen 2010). The UK joined the European Union in 1975 and Mrs. Thatcher (alongside Jacques Delors) helped build the Single Market in the early 1990s. This helped standardize regulations reducing the non-tariff (as well as tariff) barriers across a large swathe of manufacturing. Tariff barriers against European firms fell from 11% to zero after joining the EU. Having a larger market helped grow exports as well as providing competitive intensity. We show that the car industry has started to decline again after vote to leave the EU in 2016.

A third important factor has been the reduction in industrial disputes. The number of days lost to strikes has declined from a peak of 27 million in 1984 to around 270,000 in 2018, which has gone alongside a weakening of union power and influence.[5]

Finally, there is general technical change in auto manufacturing, alongside increased managerial know-how as the "Toyota Production System" of lean management diffused globally. But we show below that the improvements in the UK were particularly strong, suggesting that this is not the sole driver. Arguably, FDI, competition and better industrial relations helped speed up the spread of such technological and managerial know-how faster in the UK than elsewhere.

We first use firm-level financial data to provide a more detailed account of the auto industry's turnaround. We find intermediates increased substantially as a fraction of total costs, providing evidence that an increasing amount of production in the sector has become outsourced in line with the rise of global value chains. We also find evidence of considerable automation in the industry, with large declines in employment and increases in capital intensity. To account for these changes in factor inputs, we examine trends in total factor productivity (TFP), and continue to find the car manufacturing industry outperformed the rest of manufacturing with TFP rising by roughly twice as much between 1980 and 2018.

After documenting the relatively strong performance of British auto manufacturing, we focus whether this benefited workers in the industry via their pay. Using worker panel

4. Note that the UK also has a thriving small volume high end "luxury" market (e.g. McLaren and Aston-Martin). Some of these remain UK owned (e.g. Morgan).

5. Figures taken from Office for National Statistics 'Labour disputes; working days lost due to strike action'.

data spanning over three decades, we find the wage premium for car workers relative to the rest of manufacturing has increased substantially since the 1980s. The raw wage premium in autos compared to the rest of manufacturing was 18 log points in the 1980s, but doubled to 37 log points in the 2010s. Controlling for observable characteristics and unobservable worker fixed effects to address issues of workforce composition, reduces this premium to 8.2 log points (8.5%) in the 1980s. But this composition corrected value, still doubled to 15.7 log points (17%) in the 2010s. In contrast, the manufacturing wage premium over the rest of the economy has been stable at around 5%.

In the final part of the paper we present a simple rent-sharing model of wage determination to examine the relationship between the car wage premium and productivity changes. This framework allows us to decompose changes in the car wage premium into portions due to differential worker bargaining and to differential productivity growth. About 63% of the growth in the auto pay premium appears to be related to the growth of relative productivity, and various robustness tests conclude that productivity growth accounts for at least a half. In line with other work (Bell et al. 2019; Stansbury and Summers 2020), we find that rent-sharing has fallen over time, and this has been stronger in autos than elsewhere in manufacturing. Hence, increasing relative bargaining power cannot explain the growth of wages. If bargaining power had remained at 1980 levels, we calculate that the car premium would be about 38% higher than we observe.

In the following section we use firm-level data to document the strong performance of UK auto manufacturers relative to the manufacturing sector as a whole between 1980 and 2018. Section 3 examines the evolution of wages using worker-level panel data before section 4 outlines a framework to examine the relationship between the trends documented in the two preceding sections. Section 5 concludes. Before this we briefly discuss our contribution to the literature.

### Related literature

As noted, our paper contributes to the evidence on imperfect competition in the labour market. Many papers have documented evidence that firm effects are an important part of wage determination (Abowd et al. 1999; Card et al. 2013; Card et al. 2018; Bonhomme et al. 2023). Moreover, positive shocks to firms are partially passed through to pay and this is a feature of many countries and datasets (Guiso et al. 2005; Carlsson et al. 2016; Friedrich et al. 2019).[6] The rise in wage inequality has an important firm component (Song et al. 2019; Faggio et al. 2010) and recent research suggests that industry may be the dominant part of this firm effect (Haltiwanger et al. 2022). Our work picks up from this industry specific element, focusing on a particular industry where there has been a very strong secular increase in productivity over a number of years. Thus we relate

6. There is substantial controversy over which is the appropriate imperfect competition model (Van Reenen 2024). Much recent work has focused on monopsony reasons (Manning 2011; Berger et al. 2022; Lamadon et al. 2022; Deb et al. 2023). An earlier literature focuses on bargaining rather than these wage posting models, either from individual search and matching (Mortensen and Pissarides 1994; Postel–Vinay and Robin 2002) or collective bargaining (Kalecki 1938; Leontief 1946; Van Reenen 1996).

to the older literature on efficiency wages and inter-industry wage differentials (Krueger and Summers 1988).

A second literature we contribute to relates to productivity dynamics. Our accounting decompositions of productivity show the relative performance of the auto industry broken down into factor inputs and TFP. We also demonstrate that, contrary to much of the existing literature, this phenomenon occurs predominantly within establishments rather than between them, at least in the post-2000 period. We find some evidence of the rise of superstar firms, however, which is a pattern observed in many other sectoral and national contexts Autor et al. (2020).

Finally, we contribute to understanding the auto industry, a sector that has been the focus of much work, especially by IO economists (Berry et al. 1995). Unlike previous work, which tends to focus on issues of product market power, we make a novel contribution in examining the impact of productivity shocks on pay in this industry (we examine price-cost markups in the auto industry in more detail in a companion paper, Norris Keiller et al. 2024).

# 2 Productivity trends in UK auto manufacturing since the 1970s

## 2.1 Data

We start by documenting aggregate trends in the performance of UK auto manufacturers. We focus on data from firm surveys conducted by the Office for National Statistics (ONS): the Annual Business Survey (ABS, since 2008), the Annual Business Inquiry (ABI, 1998-2007) and the Annual Census of Production (ACP, 1980-1997).[7] We focus on comparing the auto manufacturing industry (defined as firms with the industry code 'Manufacture of Motor Vehicles')[8] and compare this primarily with manufacturing (as well as the broader market economy). Our main sample covers roughly four decades, 1980-2018. To put our results in a broader historical context, we also consider an extended sample for labour productivity which starts in 1973. Note that for the period before 1980, the industry classification does not allow us to distinguish between the manufacturing of cars and of car parts, which motivated us to start the main sample in 1980.[9]

We use this data to show how the productivity of auto manufacturers (both labour productivity and TFP) evolved and compare these trends to those in the wider manufacturing sector.[10] We focus on the comparison with the rest of manufacturing as the

7. These surveys contain annual information on firms' turnover, intermediates and value added. Further details on the data and the construction of the sample are described in more detail in Appendix A.

8. The 'Manufacture of Motor Vehicles' industry category includes commercial in addition to personal vehicles. While this is clearly a distinct market, which may complicate the interpretation of our analysis, the majority of production in the sector is personal vehicles.

9. In addition, there is also a structural break in the wage variable.

10. In the following section on worker outcomes we also use this data to examine changes in the labour share and relative wages.

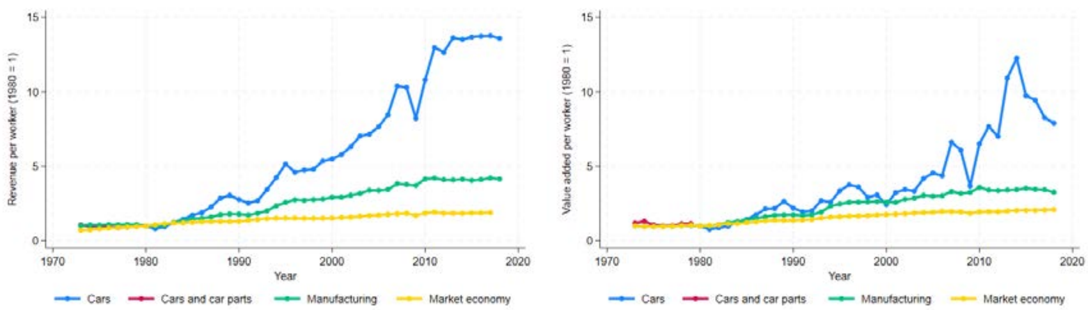
relative size of this sector has been in general decline, especially in terms of jobs, so it seems like a reasonable benchmark.

## 2.2 Industry-level productivity trends

Figure 1 shows the impressive productivity performance of the UK auto industry since 1980.[11] In Figure 1a, we show real gross output (i.e. turnover) per worker, a measure for labour productivity. While we normalise productivity to 1 in 1980, the figure also shows the broader historical trend by including the period starting in 1973, which is the earliest year of the data.[12] We see the problems discussed above in the 1970s and early 1980s with productivity stagnating both in absolute terms and relative to the rest of the economy. Output per worker fell from £64,000 in 1973 to £60,000 in 1980 (these are deflated by an auto-producer price industry deflator and expressed in 2022 prices). Productivity starts to increase after this period in a secular way, peaking in the mid-2010s around the time of the Brexit referendum in 2016. At the end of the sample period in 2018, output per worker had risen by a factor of 13 compared to 1980, standing at £819,000 albeit with a sharp fall in the 2008-9 financial crisis. If we compare this to manufacturing as a whole over the same four decades, output per worker only rose by a factor of 4. In 1980 manufacturing productivity was £75,000 and rose to £312,000 in 2018. Thus, the auto industry had a labour productivity growth rate more than three times that of manufacturing as a whole. Labour productivity rose even more slowly in the wider market economy, continuing the usual trend of non-manufacturing having slower measured productivity growth (Baumol and Bowen 1965).[13]

Figure 1: Labour Productivity Growth

(A) Real Gross Output per Worker (B) Real Gross Value Added per Worker



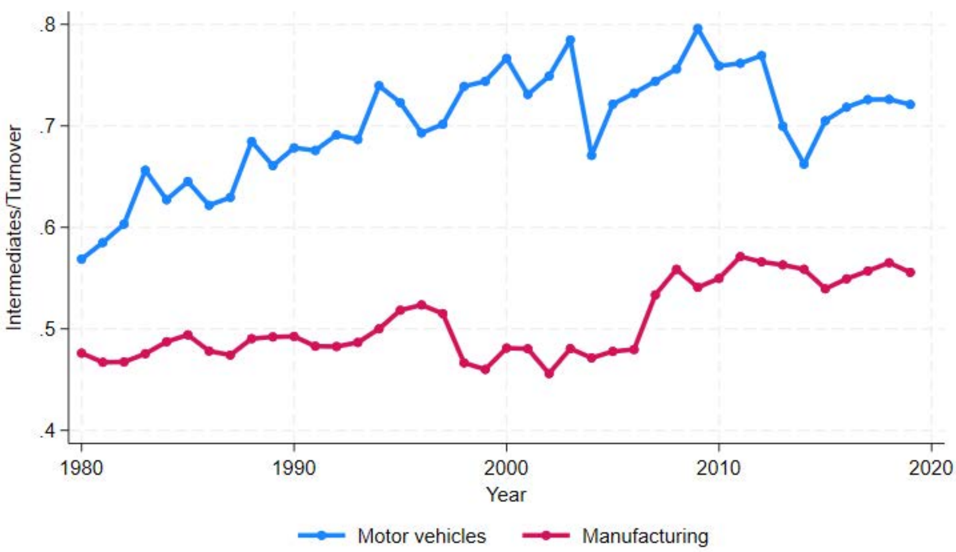

Note: panel (A) shows productivity in terms of gross output per worker for the car industry, manufacturing and the market economy. Gross output is measured as turnover. Values are normalised to 1 in 1980. Panel (B) shows the identical figure for value added per worker.

11. The underlying values are reported in Table 9 of Appendix B.
12. We report the values prior to 1980 separately as the industry classification in this early period does not distinguish the manufacture of cars from the manufacture of car parts.
13. The data for the market economy is taken from KLEMS which is derived from UK industry data, as the ABI/ABS does not contain information on the non-production sector before 1998.

One reason underlying output growth is the growth of intermediate inputs used. Outsourcing, especially internationally, was a key feature of the business landscape over this period and the auto industry is often the poster child for the globalisation of supply chains (Baldwin, 2012). To address this, we plot an alternative measure of labour productivity, value added (VA) per worker, in 1b. This strips out intermediate inputs from output. This series is a bit more volatile but still rose by a factor of 8 between 1980 and 2018 compared to a factor of 3 in manufacturing as a whole, and an even slower amount in the whole market economy. This improvement is especially pronounced after 2000. Hence, although the growth of outsourcing (mainly reflecting the growth of global supply chains) is an important part of the story of increased output per worker, it does not fully explain the overall growth, especially in the first two decades of the twenty-first century.

Another way of seeing this change is to look at the ratio of the costs of intermediate inputs in total nominal gross output. We show this in Figure 2. The ratio was already much higher than the rest of manufacturing initially, but has also has risen strongly since 1980 (from under 60% to about 70%), with the growth flattening off after 2000.

Figure 2: Intermediate Input Revenue Share




Note: This figure shows aggregate purchases of intermediate goods as a fraction of aggregate revenue.

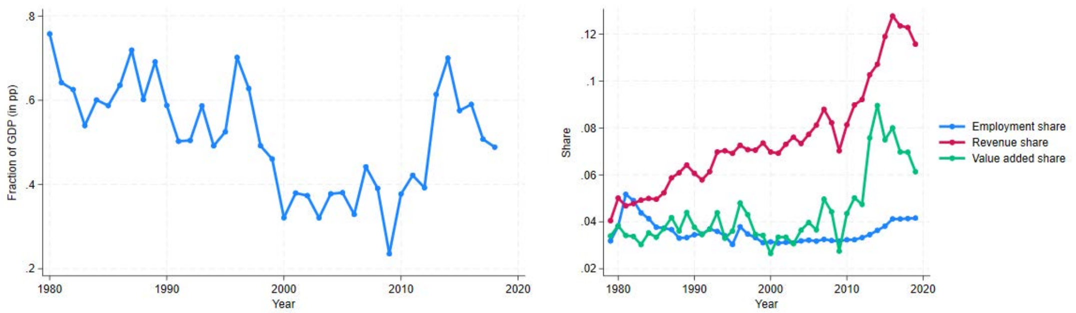
We can see these broad trends in several other ways. Figure 3a shows auto manufacturing value added as a share of the UK's whole-economy GDP. The share is 0.5% in 2018, which is similar to the level in 1990 and a decline relative to 0.75% in 1980.[14] This largely reflects the decline of manufacturing as a whole, however. Figure 3b shows the revenue share of auto manufacturing in overall manufacturing has risen from just

14. Unlike the 'market economy' series, GDP includes finance and the non-market sectors.

over 5% to just under 12% over the four decades - more than a doubling. The growth of value added has been slower (consistent with Figure 1b), from just under 4% to just over 6%. By contrast, the share of jobs has remained stable over this period at around 3.5%. Hence, the growth of productivity has not resulted from a mass shedding of labour - at least compared to the rest of manufacturing.

Figure 3: Relative Size of the Auto Manufacturing Industry

(A) Autos Relative to GDP (B) Autos Relative to Total Manufacturing

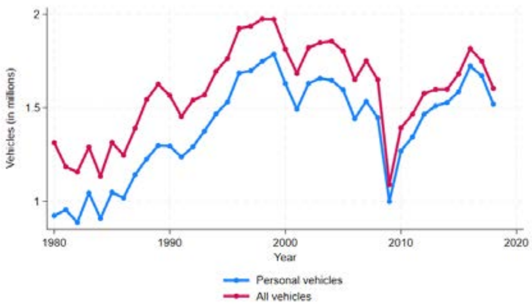



Note: panel (A) shows aggregate value added in the auto manufacturing industry as a fraction of GDP. Panel (B) plots aggregate revenue, employment and value added in auto manufacturing relative to the corresponding aggregate value in overall manufacturing.

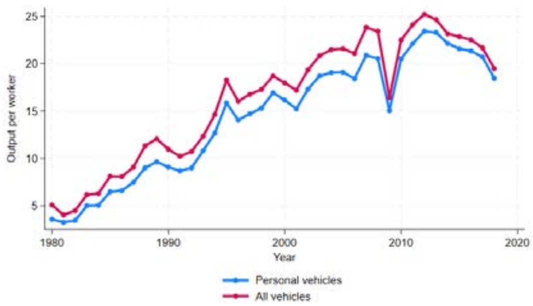
The auto series in Figure 3 is deflated using auto-specific prices, which may raise concerns over the accuracy of the price deflator. We therefore also draw on industry estimates of the number of vehicles produced provided by the Society of Motor Manufacturers and Traders (SMMT), a trade organisation for the UK's motor industry, as a complementary way of analysing productivity. Figure 4b first shows that the quantity of vehicles produced in the UK has increased between 1980-2018 (from 1.3 million in 1980 to 1.6 million in 2018). The figure supports the notion that increases in the quantity of vehicles have contributed to productivity growth rather than being primarily driven by producing fewer but more expensive cars. Figure 4b also illustrates that this quantity-based measure of output per worker has increased four-fold (from 5.1 vehicles per worker in 1980 to 19.5 in 2018). This is smaller than the six-fold increase in value added per worker, but still substantial.

Figure 4: Physical Output and Output per Worker

(A) Number of Vehicles Produced




(B) Vehicles per Worker




Note: panel (A) shows the number of vehicles (cars and commercial vehicles) produced by. The data corresponds to industry estimates from the Society of Motor Manufacturers and Traders (SMMT), in particular from *The motor industry of Great Britain centenary book* (1980-1995) and the SMMT vehicle production press releases (1996-2018). Panel (B) shows the number of vehicles per worker using the industry estimates of output together with the employment information from the ABI/ABS.

One reason for the strong growth in value added per worker are increases in capital intensity. To investigate this we calculate the growth in Total Factor Productivity (TFP). We measure TFP growth for industry $k$ in year $t$, $\Delta TFP_{kt}$, by a superlative index derived from the translog production (Caves et al. 1982; Griffith et al. 2004):

$$\begin{aligned}\Delta TFP_{kt} =& \Delta \log \Big(\frac{VA_{kt}}{VA_{kt-1}}\Big) - \frac{1}{2}(\alpha_{kt} + \alpha_{kt-1}) \Delta \log \Big(\frac{L_{kt}}{L_{kt-1}}\Big) \\ & - \Big(1 - \frac{1}{2}(\alpha_{kt} + \alpha_{kt-1})\Big) \Delta \log \Big(\frac{K_{kt}}{K_{kt-1}}\Big)\end{aligned}$$

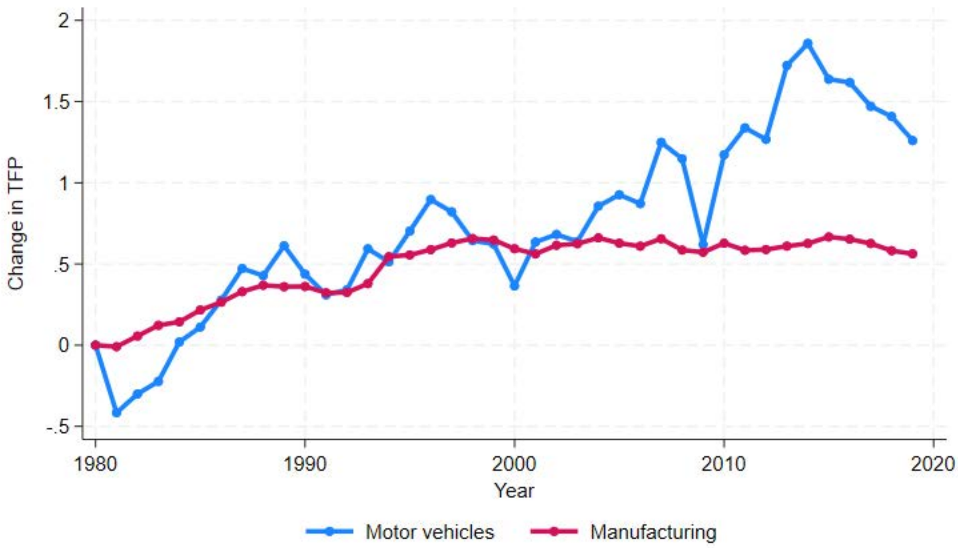
This formulation computes TFP growth as the difference between real value added ($VA$ growth and (weighed) labour ($L$) and capital ($K$) input growth, where the weight ($\alpha$) is the labour cost share of nominal value added. We allow the labour share to vary over time and across industries, which is important as there has been a decline in the manufacturing labour share. To implement this decomposition, we draw on ONS estimates of productive capital stocks by industry.[15]

Figure 5 shows the trends in TFP in auto and manufacturing industries. The main result is that productivity has grown faster in the auto industry than in manufacturing as a whole when looking at TFP. This indicates the stronger growth in labour productivity does not solely reflect increasing capital intensity. Auto TFP has risen by 1.2 compared to 0.5 in manufacturing as a whole, again with much of the growth happening after

15. We combine published numbers on productive capital stocks from two sources: one is a historical time series between 1980 and 2010 and the other is the most recent 'VICS' release which also covers the more recent time period. Note that due to differences in methodology over time, there is a level shift in these time series in 2010. We correct for this by adjusting the level of the post-2010 data so that it exactly matches the historical time series in 2010.

2000.[16]

Figure 5: Total Factor Productivity




Note: This figure compares TFP between motor vehicles and manufacturing. We construct TFP using the index number approach of Caves et al (1982).

The strength of productivity growth in the auto industry is not common to all advanced countries. The UK turnaround stands out as a remarkable one, especially after many decades of relative decline. According to OECD data for the period 1995-2018, the increase in productivity (real value added per worker) in the 'Manufacture of motor vehicles, trailers and semi-trailers' sector was higher in the UK than in the US, Germany, France, Italy and Spain.[17]

## 2.3 Firm-level decompositions

To better understand the reasons behind the increases in productivity, we decompose productivity growth by firm, exploiting the firm-level data on value added per worker. The first decomposition is a shift-share approach that distinguishes aggregate productivity growth due to within-firm growth, reallocation of employment shares towards more productive firms and entry/exit. We follow Foster et al. (2001) in using the decomposition

16. We also examined TFP through a number of other methods, such as estimating industry specific production functions, which do not impose constant returns to scale. These approaches generate results consistent with the broad trends reported here, which are available from the authors on request.

17. The data for this comparison comes from *OECD.Stat*. We apply the UK auto-specific deflator to all countries to make sure that differences are not driven by differential deflation.

$$
\begin{aligned}
\Delta z_t &= \underbrace{\sum_{i \in \mathrm{S}} e_{it-1} \Delta z_{it}}_{\text{Within-firm}} + \underbrace{\sum_{i \in \mathrm{S}} (z_{it-1} - z_{t-1}) \Delta e_{it-1} + \sum_{i \in \mathrm{S}} \Delta z_{it} \Delta e_{it}}_{\text{Reallocation}} \\
&+ \underbrace{\sum_{i \in \mathrm{Entry}} (z_{it} - z_{t-1}) e_{it} - \sum_{i \in \mathrm{Exit}} (z_{it-1} - z_{t-1}) e_{it-1}}_{\text{Net entry}},
\end{aligned}
$$

where $z_{it}$ is value added per worker of firm $i$ in year $t$, $e_{it}$ is an employment weight (the share of jobs in the industry), and $S$ indicates that a firm survived between year $t$ and $t-1$. $z_t$ is the average productivity across all firms.[18]

Figure 6 shows the results from this exercise. Productivity growth is almost entirely driven by within-firm productivity growth: reallocation of activity towards more productive firms and entry/exit only play a negligible role in the industry.[19] The dominance of the within-firm component of productivity growth may seem surprising in the light of the reallocation literature which stresses between-firm components.[20] This suggests the growth of productivity in the auto manufacturing sector comes from improvements within firms rather than employment becoming more concentrated in the most productive firms or changing employment shares across firms due to M&A and other competitive reshuffling of assets. We also performed the decomposition using firm-level TFP instead of labour productivity and obtain very similar results.[21]

18. The decomposition is motivated by the fact that aggregate labour productivity can be rewritten as the employment-weighted sum of firm-level labour productivity (with $VA_i$ being value added of firm $i$ and $E_i$ the number of employees):

$$\frac{\sum_i VA_i}{\sum_i E_i} = \sum_i \frac{VA_i}{E_i} \frac{E_i}{\sum E_i}$$

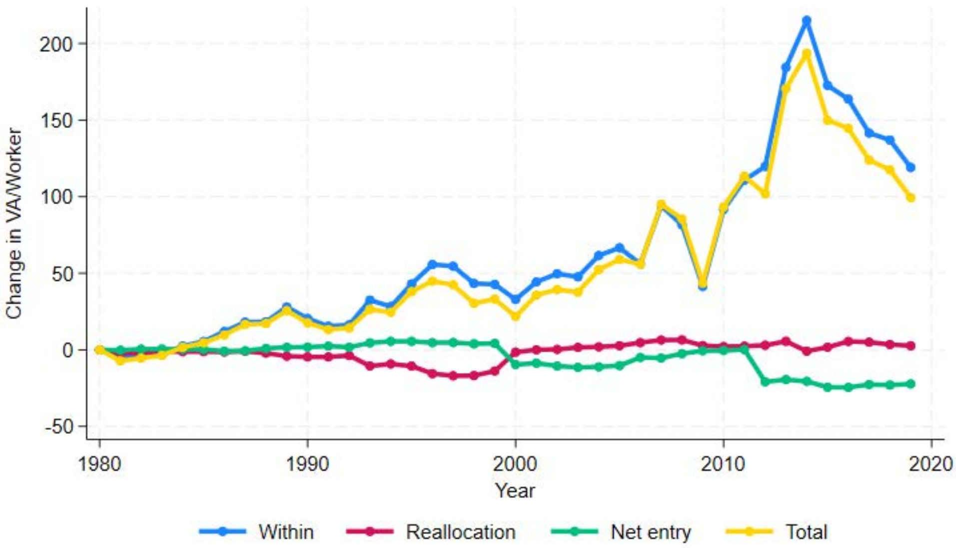
As a result, the decomposition directly corresponds to the earlier plot about aggregate productivity growth shown in Figure 1b.

19. In Appendix B we show that in manufacturing as a whole, net entry/exit plays a more important role. Note that since the data is a sample of firms rather than the population, the entry/exit component in the decomposition also picks up changes in sample composition, which is important to keep in mind in terms of the interpretation.

20. Note that the ABI/ABS samples firms at the level of *reference units*. This is a collection of establishments and a single enterprise can have multiple reference units. The decomposition in Figure 6 is performed at the level of reference units. For robustness, we also aggregated the data to the enterprise-level, which also shows the increase is driven by the within-component.

21. In Appendix B, we also examine Olley-Pakes (OP) style static decompositions instead of the dynamic shift-share approach discussed above. The OP decompositions show that large firms play a significant role in driving the rise of productivity in the auto industry after 2010.

Figure 6: Shift-Share Decomposition of Labour Productivity Growth (VA/Worker)




Note: The figure shows the result from a shift-share decomposition, which decomposes aggregate productivity growth into within-firm growth (Within-firm), reallocation of employment towards high-productivity firms (Reallocation), and entry/exit (Net entry). Total shows the overall productivity growth. See main text for definitions.

### 2.4 Summary on auto productivity

Drawing on numerous datasets, the analysis of this section documents a tremendous increase in real output per worker in the UK auto industry relative to the rest of manufacturing and the economy as a whole. Much of this increase is due to outsourcing (a higher share of intermediate inputs in revenues) and increased capital intensity. Nonetheless, TFP has increased about three times as fast in autos than the rest of manufacturing between 1980 and 2018, which has not been due to improvements in productivity within firms rather than a reallocation towards more productive firms.

## 3 The auto wage premium

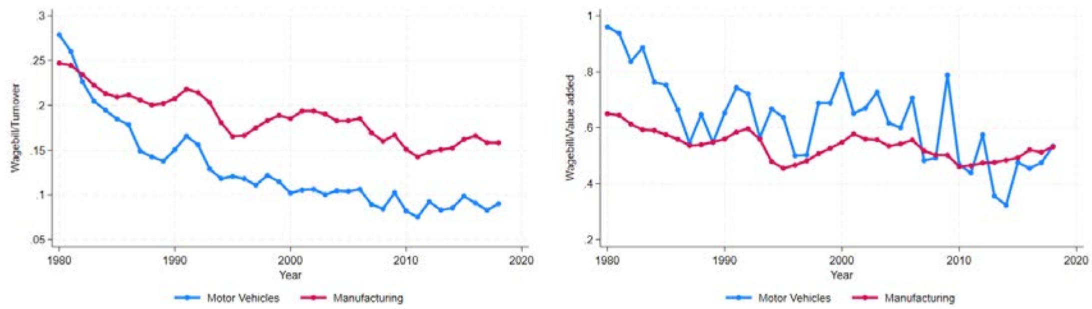
The previous section showed that UK firms in the auto manufacturing sector have experienced far stronger productivity growth than firms in the rest of manufacturing. We now examine the extent to which this has benefited auto industry workers in the form of higher wages.

## 3.1 Wage differences based on firm-level data

Figure 7 plots the share of wages in revenue (panel A) and value added (panel B). Wages are measured from the perspective of firms as total employment costs.[22] Labour's share of revenue fell markedly in the 1980s and 1990s from 28% to about 10%, after which it remained relatively stable. It has declined even more markedly in terms of value added: while labour captured nearly all of the auto industry's value added in 1980, by 2018 this had fallen to less than half. Labour shares in manufacturing have also declined since the 1980s, but much less dramatically (see Teichgraeber and Van Reenen 2021).

Figure 7: The Labour Share

(A) Labour Share of Revenue (B) Labour Share of Value Added



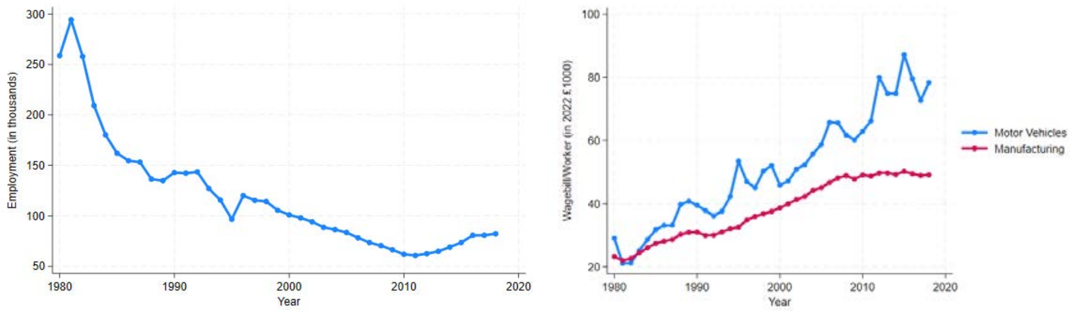

Note: panel (A) shows the labour share of revenue (total employment costs divided by total revenue). Panel (B) shows the labour share of value added.

Falls in the labour share do not necessarily imply reductions in workers' wages. Indeed, Figure 8 shows the decline in car industry labour share is exclusively due to reductions in the industry's workforce. We observe in panel (A) that the number of employees has fallen from a quarter of a million in 1980 to 82,000 in 2018 (with the bulk of this happening before the mid 1990s). The average labour costs of the remaining workers, by contrast, have actually pulled away from those in the rest of manufacturing, as shown in panel (B). In the early 1980s, average compensation was about £25,000 in both autos and manufacturing (in 2022 prices). Four decades later in 2018, average compensation had risen to about £78,000 in the auto industry compared to £49,000 in manufacturing more generally.

22. Total employment costs include workers' compensation, national insurance contributions, pensions and redundancy costs.

Figure 8: Workforce and Average Wages

(A) Number of Employees (B) Real Average Wages




Note: panel (A) shows the number of employees in the auto manufacturing industry. Panel (B) shows aggregate wages (measured as firms' total employment costs) relative to the number of workers, deflated to 2022 prices using the CPI deflator.

### 3.2 Wage differences based on individual-level data

Our results so far are based on firm and industry data, without tracking the characteristics of workers. One explanation of the auto wage premium documented in panel (B) of Figure 8 may simply be that auto manufacturers employ more skilled workers than in the rest of manufacturing. Additionally, this skill difference may have increased over time. Alternatively, workers in auto manufacturing may work longer hours, leading to a smaller *hourly* wage premium than that observed in the firm data, which is based on annual wages. To examine this issue we use the New Earnings Survey Panel Dataset (NESPD), which combines the Annual Survey of Hours and Earnings (ASHE) with its predecessor, the New Earnings Survey (NES), linking individual workers across datasets to facilitate panel analysis (Office For National Statistics 2022). The data contains information on a 1% random sample of UK employees, selected by the last two digits of their National Insurance number (the UK equivalent of a US Social Security number) assigned to all workers upon labour market entry. It covers both public and private sectors.[23]

Our analysis uses data from the period spanning 1982 to 2018. While the NESPD contains data from 1975, it is not possible to distinguish workers in the auto manufacturing industry from those working in auto part manufacturing until 1982. Figure 11 in Appendix B shows auto part workers are consistently lower-paid, so this distinction matters. [24]

23. It excludes the self employed and employees paid less than the threshold for national insurance payroll tax.

24. We end our sample period in 2018 as, although there is 2019 information in ASHE, we want to be consistent with the ABI/ABS analysis used in the previous section. Moreover, there appears to be a large decline in the number of car workers and their average wages (see Figure 12 in Appendix B), which is likely due to the ASHE survey week in 2019 coinciding with a period of temporary Easter closures in the industry.

Table 1 contains summary statistics of our sample, overall and by decade. This shows average real wages across all sectors increased between the 1980s and the 2000s, but fell back in the 2010s due to the prolonged period of low wage growth following the global financial crisis. The workforce has become progressively older since the 1980s (an average of 38 in the 1980s compared to 41 in the 2010s), while the gender balance has become more equal (42% were women in the 1980s compared to 52% in the 2010s). Average working hours have steadily fallen (from 35 to 32 hours per week) and, in tandem, the prevalence of part time working has risen (from 17% to 31%. The public sector's share of the workforce has fallen considerably from an average of 37% to 25%.

Table 1: Sample Summary Statistics (All Sectors)

| | 1980s | 1990s | 2000s | 2010s | 1982-2018 |
|---|---|---|---|---|---|
| Age | 38.07 | 38.56 | 40.03 | 40.83 | 39.43 |
| Female (%) | 0.42 | 0.46 | 0.50 | 0.52 | 0.48 |
| Public (%) | 0.37 | 0.29 | 0.26 | 0.25 | 0.29 |
| Part time (%) | 0.17 | 0.21 | 0.26 | 0.31 | 0.24 |
| Weekly wage (£2022) | 413 | 510 | 623 | 586 | 538 |
| Basic hours | 34.87 | 34.05 | 33.00 | 32.19 | 33.42 |
| Hourly wage (£2022) | 11.18 | 14.35 | 18.27 | 17.63 | 15.67 |
| N weekly wage | 1,296,533 | 1,585,909 | 1,531,875 | 1,576,280 | 5,990,597 |
| N hourly wage | 1,082,329 | 1,381,040 | 1,433,530 | 1,496,955 | 5,393,854 |

Note: table shows mean characteristics of workers in the NESPD by time period denoted in the column title (note "1980s" is 1982-1989, "1990s" is 1990-1999, "2000s" is 2020-2009 and "2010s" is 2010-2018). All statistics and sample sizes are unweighted.

We distinguish workers in the auto manufacturing and other manufacturing sectors based on the industrial code of their employer.[25] Table 2 shows average characteristics among workers in auto manufacturing and other manufacturing in the first and last decade of our sample period.[26] As seen at the industry level, the average worker in car manufacturing earned a slightly higher hourly and weekly wage than workers in other sectors in the 1980s, whereas in the 2010s they earned considerably more. For example, the increase in the hourly wage was £11.64 for auto workers compared to only £6.62 for other manufacturing workers. Looking at observable characteristics, aging in the auto industry has been a bit slower than in the rest of manufacturing, but the evolution of

25. The NESPD contains information on several different industrial classifications over different sample periods. From 1982 to 1995 the NESPD records information using the 1980 Standard Industrial Classification (SIC), from 1996 to 2008 the 1992 SIC and from 2009 onwards the 2007 SIC. Auto manufacturing workers as defined using industry code 3510/34100/29100 under the 1980/1992/2007 SIC. We define manufacturing workers using industry codes 2210-2959/15110-36639/10110-32990 under the 1980/1992/2007 SIC.

26. Table 11 in Appendix B shows the same statistics for the non-manufacturing private and public sectors.

female workers and part-time work has been similar.[27]

Table 2: Summary Statistics by Manufacturing Sector

| | 1980s | | 2010s | | Change | | |
|---|---|---|---|---|---|---|---|
| | Cars | Other Manuf. | Cars | Other Manuf. | Cars | Other Manuf. | Cars-Other Difference |
| Age | 40.98 | 38.42 | 42.86 | 43.03 | 1.88 | 4.61 | -2.39 |
| Female (%) | 0.09 | 0.28 | 0.09 | 0.25 | -0.00 | -0.03 | -0.03 |
| Part time (%) | 0.01 | 0.06 | 0.05 | 0.09 | 0.04 | 0.03 | -0.01 |
| Weekly wage (£2022) | 527 | 445 | 968 | 673 | 442 | 228 | 214 |
| Basic hours | 38.57 | 37.54 | 37.10 | 37.19 | -1.47 | -0.35 | -0.95 |
| Hourly wage (£2022) | 12.95 | 11.16 | 24.58 | 17.78 | 11.64 | 6.62 | 5.01 |
| N weekly wage | 9,617 | 350,890 | 485,729 | 5,749 | 134,839 | 485,729 | 501,095 |
| N hourly wage | 8,190 | 297,887 | 425,142 | 5,545 | 127,255 | 425,142 | 438,877 |

Note: table shows mean characteristics of workers in the NESPD by sector and time period denoted in the column title. The final three columns show the change in mean characteristics between the 1980s and the 2010s for each sector and in the difference between the auto sector and other manufacturing sector.

To quantify the auto wage premium controlling for worker characteristics, we estimate equations of the following form:

$$y_{it} = \beta_A AUTO_{it} + \beta_M MANUF_{it} + \beta X_{it} + \tau_t + \omega_w + \epsilon_{it} \tag{1}$$

where $i$ denotes workers and $t$ denotes years. $y_{it}$ is either log weekly or log hourly wages. $AUTO$ and $MANUF$ are binary variables indicating whether a worker works in the auto manufacturing industry and the general manufacturing sector respectively. $X$ are worker characteristics including age, age squared, a public sector dummy, a part-time dummy and dummies for major occupational categories. It also includes indicators for whether wages are covered by collective bargaining agreements.[28] $\tau_t$ is a full set of year dummies, $\omega_w$ are a full set of work area dummies and $\epsilon_{it}$ is a mean-zero error.[29] Below,

27. Table 10 in Appendix B shows occupational composition by sector and decade. There has been a faster growth of professional workers (up by 5 percentage points more than the rest of manufacturing) and a faster upgrading from the least skilled group (elementary) to the next level (machine operatives). Table 11 shows corresponding average wages. While the difference in average wages between car manufacturing and non-car manufacturing has increased across all occupation groups, this increase has been largest among managers and non-customer services, although the latter group accounts for a negligible share of the workforce in both sectors. Machine operatives stands out as the occupational category that has seen the biggest increase in the car manufacturing industry along with a moderately large increase in average wages relative to the same occupational category in non-car manufacturing.

28. We interact collective bargaining dummies with dummies pertaining to various periods to account for changes in the definition of collective bargaining in the NESPD.

29. 'Work areas' are a geography recorded in the NESPD which are intended to reflect local labour markets. They are distinct from, and generally larger than, 'travel to work areas' (TTWAs), which are defined using census commuting data. We use 'work areas' rather than TTWAs as the latter are not available in our data.

we shall also allow for individual fixed effects.

Table 3 shows estimates of equation 1 for log hourly wages.[30] Results are presented by decade with and without controlling for worker attributes. The main coefficient of interest is $\beta_A$, given in the row titled 'Auto manuf.'. This represents the pay premium workers in the auto manufacturing industry gain over workers in other manufacturing industries. We are particularly interested in changes over time. Columns (1)-(4) show results without controlling for worker attributes and (5)-(8) includes controls. The raw hourly pay premium in the first four columns in manufacturing compared to non-manufacturing is about 4% to 5% and is stable over the four decade period. By contrast, there is an auto premium over the rest of manufacturing of 19 log points in the 1980s, which rises to 37 log points in the 2010s. It is reassuring that the magnitude of the auto wage premium and its increase over time is not too dissimilar across decades to the results in Figure 8, which used firm-level data from an entirely different source (wage bill per employee at the firm level from the ABI/ABS firm panel). Including the observable controls in the last four columns shrinks the car premium (and mildly increases the manufacturing premium to about 6%). The fall is not dramatic, however - from 37 to 31 log points in the 2010s, for example - and the basic pattern of a large increase in the auto industry hourly wage premium is more pronounced (it was 13 log points in the 1980s and rises to 31 log points in the 2010s).

Table 3: Hourly Wage Regressions by Decade

| | (1)<br>1980s | (2)<br>1990s | (3)<br>2000s | (4)<br>2010s | (5)<br>1980s | (6)<br>1990s | (7)<br>2000s | (8)<br>2010s |
|---|---|---|---|---|---|---|---|---|
| Auto manuf. | 0.188*** | 0.260*** | 0.326*** | 0.372*** | 0.131*** | 0.223*** | 0.275*** | 0.314*** |
| | (0.007) | (0.008) | (0.010) | (0.012) | (0.006) | (0.006) | (0.008) | (0.009) |
| Manuf. | 0.036*** | 0.025*** | 0.046*** | 0.050*** | 0.059*** | 0.034*** | 0.058*** | 0.063*** |
| | (0.002) | (0.002) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| N obs. | 1,082,329 | 1,379,858 | 1,433,701 | 1,496,955 | 1,082,329 | 1,379,858 | 1,433,701 | 1,496,955 |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area FEs | No | No | No | No | Yes | Yes | Yes | Yes |
| Worker Characteristics | No | No | No | No | Yes | Yes | Yes | Yes |
| Worker FEs | No | No | No | No | No | No | No | No |

Note: dependent variable is log real hourly wage. Worker characteristics include age, age squared and dummies for occupation groups, working part time and working in the public sector. Standard errors are clustered at the worker level and reported in parentheses. */**/*** denotes significance at the 10/5/1% level respectively.

Although the auto wage premium is not explained by observable worker attributes, it may still be the case that auto manufacturing workers differ in terms of unobserved quality. To control for unobservable worker heterogeneity, we therefore include worker

30. Table 13 in Appendix B shows the equivalent for weekly wages. We focus on hourly wage results, as these are the most appropriate outcome for gauging differences in the return to labour across sectors. While we include the weekly wage results for completeness, our findings are generally similar across wage measures.

fixed effects:

$$y_{it} = \beta_A AUTO_{it} + \beta_M MANUF_{it} + \beta X_{it} + \tau_t + \omega_w + \gamma_i + \epsilon_{it} \tag{2}$$

where $\gamma_i$ are a full set of worker dummies and all other notation is the same as in equation (1).

Table 4 shows estimates of equation (2).[31] Again, results are presented by decade both with and without worker observable controls, but this time including unobservable worker fixed effects.[32]. There is evidence that some of the auto worker premium is due to higher worker unobservable worker quality in autos as the premium shrinks by about half. Column (5), for example, indicates that the hourly wage premium in the 1980s for autos was 8.5% (8.2 log points) compared to 14% (0.13 log points) in Table 3. Most importantly, however, we see the auto wage premium has grown strongly over time, rising from 8.5% (8.2 log points) in the 1980s to 17% (15.7 log points) by the 2010s. Hence, the bottom line is the car wage premium (over the rest of manufacturing) has broadly *doubled* over our four decade sample and this is true whether one uses the most rigorous controls, or the raw differentials from the individual worker or firm level data.

Table 4: Hourly Wage Regressions with Worker Fixed Effects by Decade

| | (1) 1980s | (2) 1990s | (3) 2000s | (4) 2010s | (5) 1980s | (6) 1990s | (7) 2000s | (8) 2010s |
|---|---|---|---|---|---|---|---|---|
| Auto manuf. | 0.181*** | 0.254*** | 0.323*** | 0.370*** | 0.082*** | 0.076*** | 0.113*** | 0.157*** |
| | (0.007) | (0.008) | (0.010) | (0.012) | (0.008) | (0.008) | (0.013) | (0.014) |
| Manuf. | 0.033*** | 0.020*** | 0.042*** | 0.045*** | 0.051*** | 0.049*** | 0.072*** | 0.052*** |
| | (0.002) | (0.002) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| N obs. | 1,019,222 | 1,323,441 | 1,380,549 | 1,438,525 | 1,019,222 | 1,323,441 | 1,380,549 | 1,438,525 |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area FEs | No | No | No | No | Yes | Yes | Yes | Yes |
| Worker Characteristics | No | No | No | No | Yes | Yes | Yes | Yes |
| Worker FEs | No | No | No | No | Yes | Yes | Yes | Yes |

Note: dependent variable is log real hourly wage. Worker characteristics include age, age squared and dummies for occupation groups, working part time and working in the public sector. Standard errors are clustered at the worker level and reported in parentheses. */**/*** denotes significance at the 10/5/1% level respectively.

The inclusion of worker fixed effects and an overall manufacturing dummy in equation (2) means the auto premia in columns (5)-(8) of Table 4 are identified from the wage changes that occur when workers transition into the car manufacturing industry from another manufacturing industry and vice versa. The increase in the car wage premium we see may therefore be due either to an increase in the wage gain workers enjoy when

31. The equivalent results for weekly wages are presented in Appendix Table 14.

32. The results in columns (1)-(4) without worker controls are different to the equivalent columns in table 3, as a constant sample is imposed across columns in each table and the inclusion of worker fixed effects excludes workers who are only observed once in a decade. These workers will be included in table 3 but excluded from table 4

joining the car industry or an increase in the wage loss they suffer when leaving it. To gauge which of these phenomena is the more dominant factor, we use event study regressions of the form

$$y_{it} = \sum_{l=-4}^{4} \beta_l (\text{Lag } l)_{it} + \beta X_{it} + \tau_t + \gamma_i + \epsilon_{it}, \tag{3}$$

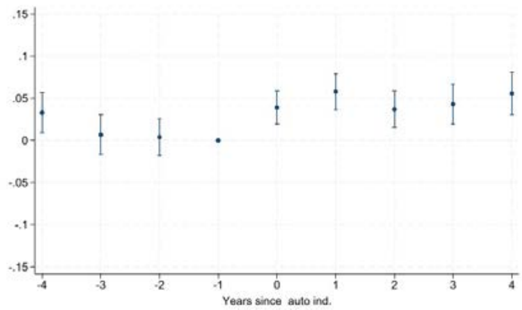
where (Lag $l$) are lags and leads around the year in which worker $i$ either joined or left the car industry and all other notation is the same as in equation (2). We cap lags and leads at four years defining these variables as $(\text{Lag } l)_{it} = \mathbb{I}[t = Event_i + l]$ for $-3 \leq l \leq 3$, where $Event_i$ is the year in which worker $i$ joined/left the auto industry, as $(\text{Lag } l)_{it} = \mathbb{I}[t \leq Event_i + l]$ for $l = -4$ and as $(\text{Lag } l)_{it} = \mathbb{I}[t \geq Event_i + l]$ for $l = 4$.[33] When estimating equation (3) to quantify entry effects we restrict the estimation sample to workers who join the auto industry from another manufacturing industry and workers who are constantly employed in the auto industry. When quantifying exit effects, by contrast, we restrict the estimation sample to workers who leave the auto industry and move into another manufacturing industry and workers constantly employed in the car industry. This means the 'control group', for whom $l_{it}$ is set to the omitted -1 'base' category, are consistently-employed auto manufacturing workers, although results are similar if we instead use consistently-employed non-auto manufacturing workers.

Figure 9 plots the $\hat{\beta}_l$ coefficients for the entry and exit specifications estimated using data from the 1980s and 2010s separately. The outcome variable in all specifications is log hourly wages, which means the coefficient point estimates can be interpreted as the approximate % difference in log hourly wages in the years before and after exit/entry to the auto manufacturing industry relative to workers that were consistently employed in the auto industry throughout the reference period. Panel (A) shows that a worker that joined the auto industry from another manufacturing industry in the 1980s was paid an hourly wage around 5% higher than consistently-employed auto workers, with this difference remaining roughly constant from the year they joined. Panel (B) shows the initial wage boost enjoyed by entrants in the 2010s is similar at around 5% in the year they joined the auto industry but, unlike in the 1980s, it grows over subsequent years to reach around 10% three years after joining.

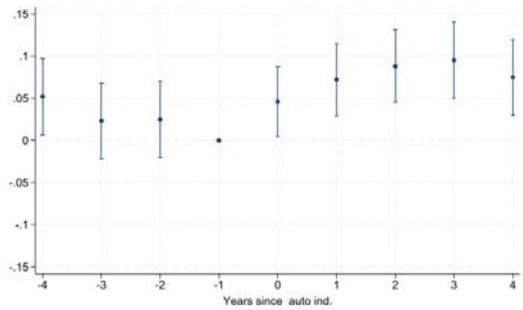
33. We omit area dummies from equation (3) for computational reasons and justify the omission with recourse to a considerable body of research that documents workers, particularly manufacturing workers, have low geographical mobility (Autor et al. 2014).

Figure 9: Hourly Wage Event Study Analysis

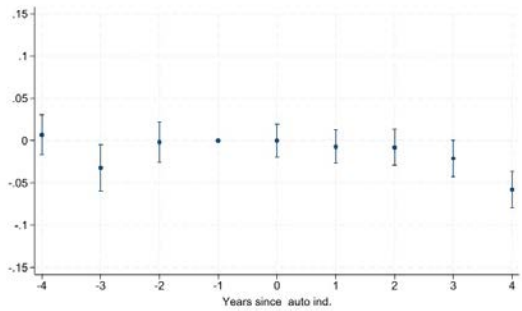
(A) 1980s Entry Hourly Wage Effects



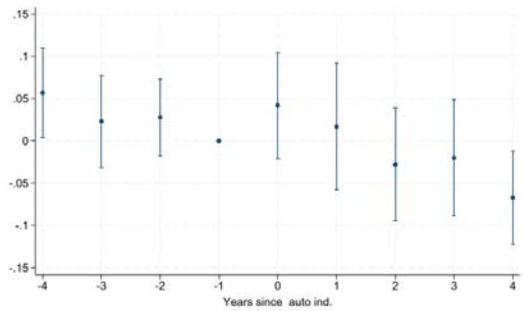

(B) 2010s Entry Hourly Wage Effects




(C) 1980s Exit Hourly Wage Effects




(D) 2010s Exit Hourly Wage Effects




Note: Figures show point estimates and 95% confidence intervals for the entry/exit lead and lag variables of specification 3. Sample sizes are 9,069 for panel 9a, 5,749 for panel 9b, 14,708 for panel 9c, and 4,386 for panel 9d. All panels additionally control for worker characteristics and worker and year fixed effects.

Panels (C) and (D) present similar estimates for workers that exit auto industry. This shows wage declines among workers that leave the auto industry versus workers that remain only become significant four years after the exit transition. This is the same in the 1980s and the 2010s, with the magnitude of the loss similar across decades at around 6%. The relative similarity of the exit effects between the 1980s and the 2010s in comparison to the entry effects across decades suggests the increase in the auto wage premium documented above is more the result of increases in the wage gain of new entrants to the auto industry rather than an increase in the wage penalty of exiting the auto industry.

Combined with the results of the previous section showing that productivity increased in the auto manufacturing sector relative to the rest of manufacturing, the finding that quality-corrected hourly wages have also risen is consistent with the rent-sharing hypothesis we began our discussion with. This raises the question: is the increase in the auto wage premium solely due to increased productivity or has it also been influenced by changes in worker bargaining power? In section 4 we use a simple framework to quantify the contribution of these factors but first we present robustness tests to corroborate our main findings.

### 3.3 Robustness and Extensions

The industry wage premia in Table 4 are estimated using equation (2) and are hence identified from workers that move between industries. Card et al. (2023) argue this identification strategy is likely to downward bias industry premia estimates as workers who newly enter an industry are likely to work in relatively low-paying firms compared to the industry average. The authors instead propose industry wage premia be based on industry-average firm fixed effects estimated via equations of the form

$$y_{it} = \beta X_{it} + \gamma_i + \upsilon_{j(i,t)} + \epsilon_{it} \tag{4}$$

where $\upsilon_{j(i,t)}$ indicates that worker $i$ worked for firm $j$ at time $t$ and all other notation is the same as in equation (2). Equipped with estimates of firm fixed effects $\hat{\upsilon}_j$, Card et al. (2023) suggest industry wage premia are calculated as differences in within-industry average firm fixed effects. For example, the analogue of the auto wage premia $\beta_A$ of equation (2), which gives the auto manufacturing pay premium relative to manufacturing as a whole, would be calculated as:

$$\beta_A^{aARD} = \frac{1}{|AUTO|} \sum_{j \in AUTO} \hat{\upsilon}_j - \frac{1}{|MANUF|} \sum_{j \in MANUF} \hat{\upsilon}_j \tag{5}$$

where $j$ denotes firms and $AUTO$ and $MANUF$ denote the set of firms in the auto manufacturing industry and manufacturing sector respectively, meaning the || operator denotes number of firms in each industry.

Estimating equation (4) requires observing the firm that a worker is employed in. This information is only available in the NESPD from 2004 onwards, which precludes a comprehensive comparison of the wage equation results above with their equivalents estimated via the Card et al. methodology. We instead focus on the latest decade of data, spanning 2010-2018 to gauge the magnitude of the bias highlighted by Card et al. As well as the comparison on the entire 2010-2018 sample, we consider a subsample of firms with at least 100 employees, as firm effects are relatively poorly identified among firms with few employees.

Table 5 summarises average firm fixed effect estimates by sector. Overall, the implied auto premia are comparable to those obtained from the wage regressions above. For example, in the "controls" version in the third column, the auto premium (relative to manufacturing) is 18 log points which is close to the 15.7 log points in the final column of Table 4. If we use the large firm sample in the final column of Table 5, the auto premium is 16 log points so near identical to those in Table 4.

Thus, while we cannot be certain that the comparison holds for earlier decades, these results lend confidence to our finding that the auto premium has increased as the magnitude of bias that Card et al. highlight would have to be considerably greater in earlier decades than in 2010-2018 to overturn this result.

Table 5: Mean Firm Fixed Effects by Sector Compared to Industry Fixed Effects

| | Raw | | Controls | |
|---|---|---|---|---|
| | All | Emp. $\geq 100$ | All | Emp. $\geq 100$ |
| Non-manuf. | -0.02 | -0.04 | 0.00 | -0.02 |
| Manuf. | 0.10 | 0.09 | 0.08 | 0.07 |
| Autos | 0.41 | 0.39 | 0.26 | 0.23 |
| Autos - Manuf. | 0.32 | 0.29 | 0.18 | 0.16 |

Note: Table shows mean firm fixed effects from a regression of log hourly wages by sector, weighted by employment. 'Raw' indicates firm fixed effects were estimated without controlling for worker characteristics or worker fixed effects. 'Controls' indicates firm fixed effects were estimated controlling for worker characteristics (quadratic age, part-time status, occupation, collective bargaining), and worker fixed effects.

# 4 The contribution of productivity and bargaining to growth in the auto wage premium

## 4.1 Model

How much of the growth in the auto wage premium documented in section 3 is due to the improved productivity in the auto sector documented in section 2? To answer this question, we consider a simple model of wage determination

$$w_{ijt} = \alpha_{0t}^k + \alpha_{1t}^k p_{jt} + \alpha_t^k \eta_{ijt} \tag{6}$$

where $w_{ijt}$ is log wages of worker $i$ in firm $j$ in year $t$, $p_{jt}$ is a measure of firm performance (e.g. log real value added per worker), and $\eta_{ijt}$ are all other determinants of wages such as worker quality. The $k$ subscripts denotes industry, indicating that all parameters are industry-specific.

We focus on the wage premium in autos ($k = a$) compared to the rest of the manufacturing industry ($k = a'$). This can be denoted as:

$$\bar{w}_t^a - \bar{w}_t^{a'} = (\alpha_{0t}^a - \alpha_{0t}^{a'}) + (\alpha_{1t}^a \bar{p}_t^a - \alpha_{1t}^{a'} \bar{p}_t^{a'}) + (\alpha_t^a \bar{\eta}_t^a - \alpha_t^{a'} \bar{\eta}_t^{a'}), \tag{7}$$

where bars denote means calculated over workers and firms within an industry.

Adding and subtracting $\alpha_{1t}^{a'} \bar{p}_t^a$ from equation (7), we can decompose the car wage premium into components due to productivity differences and bargaining differences:

$$\bar{w}_t^a - \bar{w}_t^{a'} = (\bar{p}_t^a - \bar{p}_t^{a'})\alpha_{1t}^{a'} + (\alpha_{1t}^a - \alpha_{1t}^{a'})\bar{p}_t^a + \zeta_t, \tag{8}$$

where the residual $\zeta_t = \alpha_{1t}^a - \alpha_{1t}^{a'} + \alpha_t^a \bar{\eta}_t^a - \alpha_t^{a'} \bar{\eta}_t^{a'}$ absorbs differences in the intercept and in the difference in other characteristics that affect wages across sectors. The leading term $(\bar{p}_t^a - \bar{p}_t^{a'})\alpha_{1t}^{a'}$ is the contribution of the relative productivity difference in cars while the second term $(\alpha_{1t}^a - \alpha_{1t}^{a'})\bar{p}_t^a$, is the contribution of differences in relative bargaining power.

In our baseline estimates, we evaluate the former at the non-auto bargaining parameter and the latter at the productivity level of autos. But we also consider evaluating these terms at the auto parameter and non-auto productivity level respectively (and an average of the two) in robustness tests. Differencing equation (8) across time we obtain:

$$\Delta(w^a_{ijt} - w^{a'}_{ijt}) = \Delta[(p^a_{jt} - p^{a'}_{jt})\alpha^{a'}_{1t}] + \Delta[(\alpha^a_{1t} - \alpha^{a'}_{1t})p^a_{jt}] + \Delta\omega_{ijt}, \tag{9}$$

which we use to decompose changes in the auto premium $\Delta(w^a_{ijt} - w^{a'}_{ijt})$ into a component due to relative productivity changes $\Delta[(p^a_{jt} - p^{a'}_{jt})\alpha^{a'}_{1t}]$ and a component due to relative bargaining changes $\Delta[(\alpha^a_{1t} - \alpha^{a'}_{1t})p^a_{jt}]$.

Implementing the decomposition in equation (9) requires estimates of the $\alpha$ parameters along with data on average wages and productivity. To obtain these quantities, we use the ABI/ABS data to estimate wage equations using the specification

$$w_{jt} = \beta_0 + \beta_1 \log\left(\frac{VA}{L}_{jt}\right) + \beta_2 \log\left(\frac{VA}{L}_{jt}\right) * AUTO_{jt} + \phi_j + \tau_t + \epsilon_{jt}, \tag{10}$$

where $j$ denotes firm and $t$ denotes year. $\frac{VA}{L}$ is value-added per employee and $AUTO$ is a dummy denoting whether a firm is in the auto industry. $\tau_t$ is a vector of time fixed effects and $\phi_j$ is a vector of firm fixed effects, which are included to flexibly control for the $\eta$ terms of equation (7). Estimating this equation on a sample of manufacturing firms recovers estimates of the bargaining parameters of equation (7) as $\hat{\alpha}^{a'}_1 = \hat{\beta}_1$ and $\hat{\alpha}^a_1 = \hat{\beta}_1 + \hat{\beta}_2$.

Table 6 contains parameter estimates obtained by estimating equation (10) via OLS along with mean sample characteristics.[34] The $\beta$ parameter estimates imply rent sharing has decreased over time from 0.27 in the 1980s to 0.18 in the 2010s. This is consistent with Bell et al. (2019) who find declines in rent sharing among large publicly listed British companies. We believe that we are the first to show this for a broader sample of firms that includes non-publicly listed firms. Stansbury and Summers (2020) argue that worker power to appropriate rents has also declined substantially in the US over this period.

Table 6 also shows that bargaining power is slightly lower in the auto industry than the rest of manufacturing as $\beta_2$ is negative. Interestingly this gap has increased slightly over time, so the auto rent sharing term has dropped more than the rest of manufacturing (from 0.24 to 0.14). Hence, bargaining power cannot be an explanation for the *rising* auto wage premium.

34. To facilitate comparison with previous analysis, results in the '1980s' column are calculated using data over 1982-1989, while those in the '2010s' column are calculated using data over 2010-2018.

Table 6: Auto Wage Premium Decomposition Estimates and Sample Moments

| | (1) 1980s | (2) 2010s |
|---|---|---|
| Parameter estimates | | |
| $\beta_1$ | 0.27 | 0.18 |
| | (0.011) | (0.018) |
| $\beta_2$ | -0.03 | -0.04 |
| | (0.029) | (0.024) |
| Sample mean characteristics | | |
| Non-auto Log(Wage) | 2.89 | 3.32 |
| Auto Log(Wage) | 3.04 | 3.79 |
| Non-auto Log(VA/Emp.) | 3.17 | 3.92 |
| Auto Log(VA/Emp.) | 2.99 | 4.74 |
| Non-auto N | 104,931 | 46,283 |
| Auto N | 340 | 335 |

Note: wages deflated using CPI, value added deflated using PPI. Parameter estimates and sample characteristics are calculated weighting by firm employment. Standard errors in parentheses clustered at the firm level. Sample sizes are unweighted. Underlying regression results are presented in Appendix Table 16.

## 4.2 Results

Table 7 shows results of the wage decomposition of equation 9, implemented using the estimates and sample characteristics of Table 6. In the 1980s, differences in productivity and bargaining acted to *reduce* the wages of auto workers relative to other manufacturing workers, as indicated by the negative sign on both the productivity and bargaining components. In the 2010s, by contrast, the positive gap between productivity in the auto industry and the rest of manufacturing accounted for about a third ($\frac{0.15}{0.47}$) of the auto wage premium. Between the 1980s and the 2010s, the auto wage premium grew by 32 log points (from 15 to 47). We calculate that 63% ($\frac{0.2}{0.32}$) of this change is due to the faster growth of productivity in the auto industry. This was offset by a reduction in worker bargaining power in the sector. Had bargaining power remained at its 1980s levels, the auto wage premium would have been approximately 38% greater ($\frac{0.12}{0.32}$) than actually observed.

This decomposition evaluates the productivity contribution using the non-auto bargaining parameter and the bargaining contribution using the auto industry mean value added per worker. Table 17 in the Appendix B repeats the decomposition of Table 7 but instead evaluates the productivity contribution using the auto bargaining parameter and the bargaining contribution using the non-auto industry mean value added per worker. Under this decomposition, about 50% of the increase in the auto wage premium is due to changes in relative productivity, and the auto wage premium increase would have been approximately 25% greater had bargaining differences remained unchanged. Regardless of parameterisation, it is therefore clear that increases in auto industry productivity have significantly contributed to the widening auto wage premium and that changes in the bargaining power of workers have partially offset these gains.

Table 7: Auto Wage Premium Decomposition

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Portion due to differences in | | |
| | $\bar{w}^a - \bar{w}^{a'}$ | Productivity | Bargaining | N |
| 1980s | 0.15 | -0.05 | -0.09 | 105,271 |
| 2010s | 0.47 | 0.15 | -0.21 | 46,618 |
| Change | 0.32 | 0.2 | -0.12 | 15,1889 |

Note: column (1) shows the difference in log average wages between auto manufacturers and other manufacturers, defined as gross wages per employee. Columns (2)-(3) show the estimated components of equation 8. Column (4) shows the sample size used to calculate the wage difference and estimate the components.

This highlights that the magnitude of the productivity contribution to wages depends on the size of the bargaining power parameter. Our estimate of about 0.2 is in line with the pass through parameter of Friedrich et al. (2019), Kline et al. (2019) and Van Reenen (1996). But it is larger than those in the survey by Card et al. (2018). Obviously, using a lower bargaining parameter would reduce the share of the rising relative auto premium accounted for by rent-sharing.

# 5 Conclusion

When labour markets are imperfectly competitive, productivity shocks will be (partially) passed on to worker wages in the firms or industries experiencing these shocks. We use the UK auto manufacturing industry as a case study. After much decline into the early 1980s, we document a remarkable turnaround of productivity growth in the industry between 1980 and 2018. Labour productivity and TFP grew about three times faster in the auto industry than the rest of manufacturing, primarily through within firm growth.

Using panel data on workers and firms, we show that the wage premium in autos (compared to the rest of manufacturing) has risen alongside the productivity boom. Even after controlling for worker fixed effects, auto workers in the 1980s enjoyed a wage premium of 8.5% compared to the rest of manufacturing, whereas by the 1980s this had doubled to 17%. Our baseline estimated rent sharing model implies that the majority of the increase in the pay premium can be accounted for by productivity increases (63% in the baseline case). In contrast, we find a fall in bargaining power, implying this cannot account for the pay trends. Indeed, had worker bargaining power stayed the same, the auto pay premium would be even higher.

Our work confirms, both in a qualitative and quantitative sense, the importance of labour market imperfections. More generally it suggests that increases in productivity can benefit workers directly via higher wages, rather than solely as consumers through lower prices - even in an environment where bargaining power might be on the decline. In a companion paper (Norris Keiller et al. 2024), we examine the extent to which shareholders and consumers benefited from the productivity growth by analysing prices, model quality and price-cost markups. Broadly, we find that for cars produced in the UK, markups fell to some degree in the domestic UK market, but have risen for exports, particularly those sent to countries outside the EU. This suggests the productivity boom benefits also spread to UK consumers as well as workers.

Finally, it is worth noting that productivity seems to have been declining among UK auto manufacturers since around the time of the Brexit referendum. If this continues we predict that the pain will be felt not just in terms of jobs and profits, but also in terms of the pay of workers in the industry.

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# A Data appendix

## A.1 ACP/ABI/ABS

In this appendix, we describe the firm-level microdata in more detail. The data comes from annual surveys which have been conducted by the Office for National Statistics (ONS). The Annual Census of Production (ACP) started in 1970 and covered the production sector (manufacturing and mining). In 1998, the Annual Business Inquiry (ABI) was introduced, which contains data on the whole economy. The data between 1973-2007 is contained in Office For National Statistics (2012). In 2008, the ABI was replaced by the Annual Business Survey (ABS) (Office For National Statistics (2023)). Note that even though the ACP starts in 1970, we focus on the period after 1980 as consistent time series can only be constructed for this period due to changes in variable definition in early years.

The surveys contain a sample of firms and provide sampling weights in order to produce representative statistics. The exact implementation of the sampling scheme has changed over the years. Broadly, the surveys contain the universe of large firms (with at least 250 employees) and a random sample of smaller firms, where the likelihood of being sampled depends on firm size and region.

In terms of industry definitions, we define our sample of the auto industry through the industry code "Manufacture of Motor Vehicles". As the industry classification (UK SIC) has been adjusted over time, this refers to different industry codes:

- Code 3510 in the 1980 SIC
- Code 34100 in the 1992/2003 SIC
- Code 29100 in the 2007 UK SIC

Table 8 shows the number of observations in the auto industry and in the manufacturing sector for each year. Note that the data comes with sampling weights, as the firms in the data are typically larger than the population of all UK firms. Most notably, the drop in observations in the auto industry is 1979 is driven by a change in the sampling scheme whereby coverage of smaller firms stopped being comprehensive and instead switched to a random sampling design.[35]

Regarding variable definitions, we define value added (VA) as turnover minus intermediates. Note that the ONS in general has several alternative definitions of VA. The first is "value added at market prices", which adds to our definition (turnover minus intermediates) the following categories:

- value of insurance claims
- change in value of stocks over the year
- net value of finished capital work for own use

The second is "value added at factor cost", which further adds subsidies and net duty/excise payments and subtracts taxes relative to value added at market prices.

A final important consideration is the use of deflators to account for price changes over time. For the time period between 1996-2019, an industry-specific output price deflator time series is available from the ONS (the series "2910000000: Motor Vehicles"). For manufacturing, the ONS publishes a longer output price deflator series starting in 1957 (PPI series for "Manufactured Products for Domestic Market, Excl Duty"). In order to use the industry-specific information as much as possible while retaining coverage of the full period, we use the auto-specific deflator for 1996-2019. Before 1996, we assume the auto deflator changes with the same growth rate as the manufacturing deflator. The deflators are defined so real monetary values are expressed in 2022 prices.

35. All larger firms continued to be surveyed in each year of the survey.

Table 8: Number of Observations (ABI/ABS)

| Year | Manufacturing | Motor Vehicles |
|---|---|---|
| 1973 | 20354 | 434 |
| 1974 | 22039 | 463 |
| 1975 | 20409 | 416 |
| 1976 | 20545 | 416 |
| 1977 | 20472 | 402 |
| 1978 | 17424 | 332 |
| 1979 | 17138 | 43 |
| 1980 | 14171 | 42 |
| 1981 | 14206 | 45 |
| 1982 | 13952 | 42 |
| 1983 | 13572 | 45 |
| 1984 | 17840 | 56 |
| 1985 | 13302 | 42 |
| 1986 | 12729 | 44 |
| 1987 | 12807 | 47 |
| 1988 | 12973 | 48 |
| 1989 | 18452 | 49 |
| 1990 | 13503 | 51 |
| 1991 | 13323 | 55 |
| 1992 | 12774 | 58 |
| 1993 | 11362 | 55 |
| 1994 | 10649 | 41 |
| 1995 | 9381 | 43 |
| 1996 | 10554 | 54 |
| 1997 | 9147 | 45 |
| 1998 | 9139 | 49 |
| 1999 | 8936 | 51 |
| 2000 | 8739 | 48 |
| 2001 | 9159 | 51 |
| 2002 | 8507 | 49 |
| 2003 | 8277 | 47 |
| 2004 | 7970 | 44 |
| 2005 | 7500 | 41 |
| 2006 | 6780 | 42 |
| 2007 | 6988 | 47 |
| 2008 | 4298 | 44 |
| 2009 | 4016 | 38 |
| 2010 | 3946 | 32 |
| 2011 | 3668 | 33 |
| 2012 | 3780 | 31 |
| 2013 | 3652 | 30 |
| 2014 | 3748 | 34 |
| 2015 | 3667 | 35 |
| 2016 | 7693 | 49 |
| 2017 | 7458 | 50 |
| 2018 | 7049 | 48 |
| 2019 | 5664 | 45 |

Note: the table shows the number of observations in auto manufacturing and in overall manufacturing in our sample. Note that the ABI/ABS provides sampling weights, so that these observations represent a broader set of firms, and that the sampling scheme changes over time (in particular in 1979).

# B Supplementary results

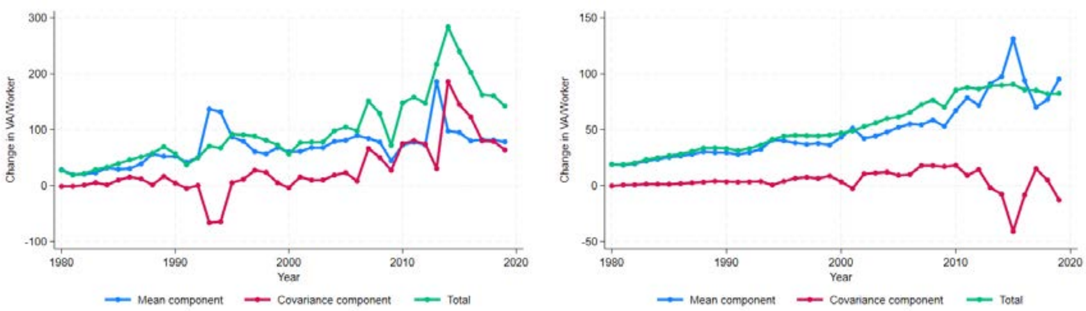
We also apply the Olley-Pakes (OP) decomposition which asks to what extent aggregate (employment-weighted) productivity is well-captured by the unweighted mean of productivity, as opposed to aggregate productivity being driven by large firms having an exceptionally high productivity. Formally, the OP decomposition expresses aggregate productivity as the sum of a mean and a covariance component:

$$z_t = \sum_i w_{it} z_{it} = \underbrace{\frac{1}{N_t} \sum_{i=1,\ldots,t}^{N_t} z_{it}}_{\text{Mean component}} + \underbrace{\sum_{i=1}^{N_t} (z_{it} - \bar{z}_t)(w_{it} - \frac{1}{N_t})}_{\text{Covariance component}}$$

Like before, $z_t/z_{it}$ are aggregate and firm-level productivity and $w_{it}$ is the employment share. $N_t$ is the number of firms in year $t$. Figure 10 shows the results. For the auto industry, aggregate productivity closely follows the unweighted mean until the late 2000s. Afterwards, the contribution of the covariance component becomes almost as significant as the mean component. This implies that the significant boom in value added per worker after 2010 is to an important extent driven by large firms who have very high productivity, which can be viewed as a "superstar firm" (Autor et al. (2020)) effect in the auto manufacturing industry. For manufacturing as a whole, by contrast, this superstar effect plays a smaller role and aggregate productivity growth is mostly close to the mean component.

Figure 10: Olley-Pakes Decompositions of Labour Productivity Growth (VA/Worker)

(A) Autos (B) Manufacturing




Note: figure shows the results from an Olley-Pakes decomposition of aggregate productivity (see main text for definition) for the auto manufacturing industry and manufacturing.

Table 9: Labour Productivity in Autos and Manufacturing

| Year | Manuf., Rev./Worker | Cars, Rev./Worker | Manuf., VA/Worker | Cars, VA/Worker |
|---|---|---|---|---|
| 1973 | 76.82 | 64.20 | 28.55 | 20.66 |
| 1974 | 80.63 | 57.53 | 27.56 | 22.97 |
| 1975 | 78.95 | 60.00 | 27.81 | 18.64 |
| 1976 | 82.44 | 56.06 | 27.66 | 17.62 |
| 1977 | 81.62 | 53.22 | 27.92 | 17.83 |
| 1978 | 83.02 | 55.89 | 29.28 | 19.85 |
| 1979 | 82.19 | 63.45 | 29.32 | 20.14 |
| 1980 | 75.35 | 60.27 | 28.61 | 17.51 |
| 1981 | 74.90 | 48.66 | 28.43 | 13.50 |
| 1982 | 81.71 | 56.82 | 31.29 | 15.38 |
| 1983 | 92.53 | 74.10 | 34.76 | 17.12 |
| 1984 | 102.39 | 87.85 | 37.02 | 22.40 |
| 1985 | 110.93 | 103.36 | 40.37 | 25.35 |
| 1986 | 114.22 | 113.58 | 43.26 | 30.47 |
| 1987 | 120.77 | 136.79 | 46.39 | 37.39 |
| 1988 | 132.13 | 171.96 | 49.12 | 37.89 |
| 1989 | 135.22 | 183.88 | 49.78 | 46.34 |
| 1990 | 134.66 | 166.55 | 49.95 | 38.37 |
| 1991 | 130.13 | 152.34 | 48.57 | 33.99 |
| 1992 | 138.96 | 162.32 | 49.96 | 35.07 |
| 1993 | 151.43 | 206.55 | 55.06 | 47.24 |
| 1994 | 176.47 | 255.83 | 66.56 | 45.30 |
| 1995 | 193.83 | 309.97 | 70.44 | 58.71 |
| 1996 | 207.20 | 278.32 | 73.94 | 65.64 |
| 1997 | 204.40 | 285.96 | 74.22 | 63.18 |
| 1998 | 207.91 | 288.83 | 74.95 | 51.12 |
| 1999 | 210.50 | 323.01 | 75.48 | 53.87 |
| 2000 | 219.31 | 330.85 | 74.14 | 42.52 |
| 2001 | 219.91 | 348.69 | 73.66 | 56.47 |
| 2002 | 230.12 | 379.82 | 79.64 | 60.19 |
| 2003 | 238.80 | 423.66 | 81.64 | 58.42 |
| 2004 | 255.28 | 431.14 | 87.25 | 73.20 |
| 2005 | 254.48 | 460.71 | 85.75 | 79.79 |
| 2006 | 259.08 | 509.93 | 86.43 | 76.62 |
| 2007 | 288.68 | 625.85 | 94.60 | 115.83 |
| 2008 | 284.61 | 620.52 | 90.59 | 106.35 |
| 2009 | 279.65 | 494.91 | 92.84 | 64.28 |
| 2010 | 312.84 | 651.03 | 102.32 | 114.02 |
| 2011 | 316.73 | 781.61 | 97.22 | 134.07 |
| 2012 | 308.96 | 763.01 | 96.42 | 122.59 |
| 2013 | 308.17 | 820.80 | 97.32 | 191.26 |
| 2014 | 311.42 | 814.30 | 98.06 | 214.34 |
| 2015 | 306.21 | 824.10 | 100.67 | 170.73 |
| 2016 | 309.91 | 827.72 | 98.76 | 165.29 |
| 2017 | 317.15 | 829.22 | 97.94 | 144.65 |
| 2018 | 312.82 | 819.08 | 93.05 | 138.17 |

Note: table shows the values of labour productivity (turnover per worker and value added per worker) for each year since 1973. Values are expressed in 2022 GBP (in 1000s).

Figure 11: Mean Hourly Wage in Auto Manufacturing Industries

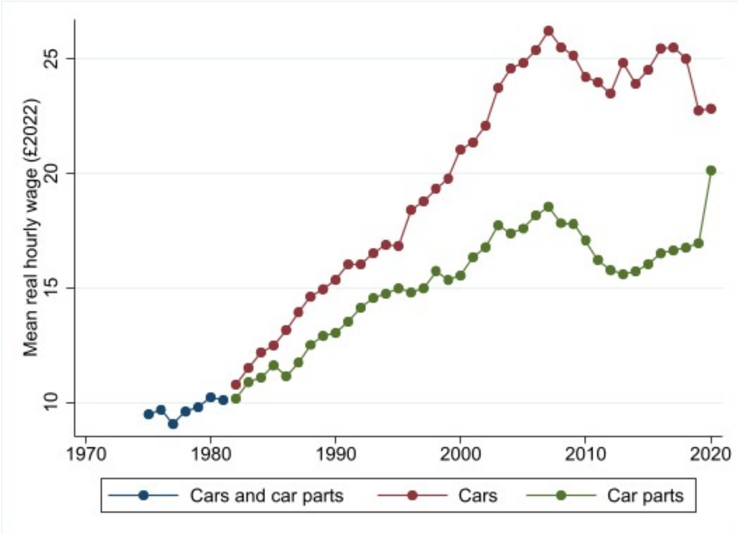
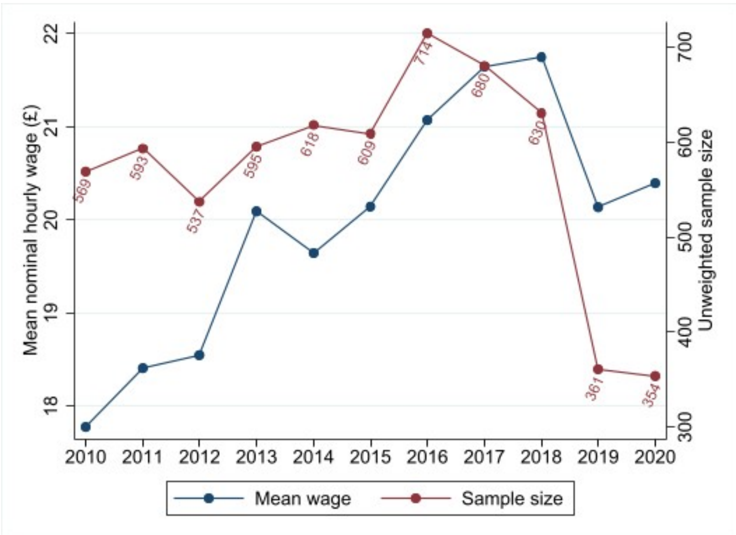



Figure 12: Auto Manufacturing Industry Mean Hourly Wage and Sample Size




Note: sample size underlying the 'Mean wage' series is shown in the 'Sample size' series.

Table 10: Occupational Composition by Sector and Decade

| | 1980s | | 2010s | | Change | | |
|---|---|---|---|---|---|---|---|
| | Cars | Other Manuf. | Cars | Other Manuf. | Cars | Other Manuf. | Cars-Other Difference |
| Managers | 0.06 | 0.07 | 0.07 | 0.09 | 0.01 | 0.02 | 0.01 |
| Professional | 0.10 | 0.09 | 0.15 | 0.10 | 0.06 | 0.01 | 0.05 |
| Assoc. Pro. | 0.11 | 0.11 | 0.09 | 0.13 | -0.01 | 0.02 | 0.03 |
| Admin | 0.06 | 0.10 | 0.04 | 0.09 | -0.02 | -0.01 | 0.01 |
| Skilled trades | 0.31 | 0.23 | 0.19 | 0.18 | -0.12 | -0.05 | -0.07 |
| Other services | 0.01 | 0.02 | 0.00 | 0.00 | -0.01 | -0.01 | -0.00 |
| Customer services | 0.03 | 0.04 | 0.01 | 0.03 | -0.01 | -0.01 | 0.00 |
| Machine ops | 0.20 | 0.20 | 0.40 | 0.22 | 0.20 | 0.01 | 0.18 |
| Elementary | 0.12 | 0.13 | 0.04 | 0.15 | -0.08 | 0.02 | 0.10 |
| N | 9,617 | 350,890 | 5,749 | 485,729 | 134,839 | 485,729 | 501,095 |

Note: table shows the share of workers in each major occupation group by sector and time period denoted in the column title. The final three columns show the change in occupation shares between the 1980s and the 2010s for each sector and the change in the difference between the car sector and other manufacturing sector.

Table 11: Occupation Real Median Wages by Sector and Decade (2022 Prices)

| | 1980s | | 2010s | | Change | | |
|---|---|---|---|---|---|---|---|
| | Cars | Other Manuf. | Cars | Other Manuf. | Cars | Other Manuf. | Cars-Other Difference |
| Managers | 15.85 | 13.69 | 35.80 | 27.06 | 19.95 | 13.37 | 6.57 |
| Professional | 15.82 | 15.22 | 31.17 | 27.67 | 15.35 | 12.45 | 2.91 |
| Assoc. Pro. | 14.78 | 12.92 | 25.98 | 22.07 | 11.20 | 9.15 | 2.05 |
| Admin | 10.97 | 11.37 | 17.00 | 15.10 | 6.03 | 3.73 | 1.50 |
| Skilled trades | 13.22 | 10.25 | 21.15 | 15.61 | 7.93 | 5.36 | 2.57 |
| Other services | 12.26 | 10.42 | 24.36 | 11.70 | 12.09 | 1.28 | 10.81 |
| Customer services | 12.83 | 10.89 | 19.37 | 14.48 | 6.54 | 3.58 | 2.95 |
| Machine ops | 12.07 | 9.11 | 21.07 | 13.41 | 9.00 | 4.30 | 4.70 |
| Elementary | 11.83 | 9.49 | 18.36 | 11.32 | 6.53 | 1.83 | 4.70 |

Note: table shows 'fuzzy' median wages by occupation, sector and decade calculated as the mean among the 50 observations closest to the median. The final three columns show the change in occupation 'fuzzy' median wages between the 1980s and the 2010s for each sector and in the difference between the car sector and other manufacturing sector. Hourly wages are deflated using the Consumer Price Index and expressed in 2022 prices.

Table 12: Summary Statistics by Sector

| | 1980s | | 2010s | | Change | |
|---|---|---|---|---|---|---|
| | Non-manuf. | Public | Non-manuf. | Public | Non-manuf. | Public |
| Age | 36.10 | 39.80 | 39.56 | 43.49 | 3.46 | 3.69 |
| Female (%) | 0.43 | 0.52 | 0.50 | 0.69 | 0.07 | 0.17 |
| Part time (%) | 0.18 | 0.23 | 0.33 | 0.32 | 0.15 | 0.09 |
| Weekly wage (£ 2022) | 399 | 401 | 558 | 627 | 159 | 226 |
| Basic hours | 34.78 | 32.78 | 31.98 | 30.97 | -2.80 | -1.81 |
| Hourly wage (£ 2022) | 10.78 | 11.58 | 16.79 | 19.66 | 6.01 | 8.08 |
| | Occupational composition | | | | | |
| Managers (%) | 0.10 | 0.06 | 0.09 | 0.04 | -0.00 | -0.02 |
| Professional (%) | 0.09 | 0.24 | 0.12 | 0.33 | 0.03 | 0.09 |
| Assoc. Pro. (%) | 0.13 | 0.11 | 0.11 | 0.15 | -0.02 | 0.04 |
| Admin (%) | 0.20 | 0.14 | 0.14 | 0.18 | -0.06 | 0.04 |
| Skilled trades (%) | 0.11 | 0.08 | 0.07 | 0.02 | -0.05 | -0.07 |
| Other services (%) | 0.04 | 0.10 | 0.09 | 0.17 | 0.05 | 0.07 |
| Customer services (%) | 0.11 | 0.05 | 0.16 | 0.02 | 0.05 | -0.03 |
| Machine ops (%) | 0.09 | 0.07 | 0.06 | 0.01 | -0.03 | -0.05 |
| Elementary (%) | 0.13 | 0.15 | 0.16 | 0.08 | 0.03 | -0.07 |
| N weekly wage | 477,375 | 458,651 | 1,050,340 | 385,352 | 1,527,715 | 844,003 |
| N hourly wage | 396,282 | 379,970 | 988,548 | 375,607 | 1,384,830 | 755,577 |

Note: table shows mean characteristics of workers in the NESPD by sector and time period denoted in the column title.

Table 13: Weekly Wage Regressions by Decade

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | 1980s | 1990s | 2000s | 2010s | 1980s | 1990s | 2000s | 2010s |
| Auto manuf. | 0.218*** | 0.289*** | 0.372*** | 0.429*** | 0.110*** | 0.190*** | 0.282*** | 0.296*** |
| | (0.008) | (0.009) | (0.011) | (0.013) | (0.008) | (0.007) | (0.010) | (0.011) |
| Manuf. | 0.204*** | 0.236*** | 0.268*** | 0.299*** | 0.076*** | 0.049*** | 0.069*** | 0.077*** |
| | (0.002) | (0.003) | (0.003) | (0.004) | (0.002) | (0.002) | (0.002) | (0.002) |
| N obs. | 1,296,533 | 1,584,673 | 1,531,867 | 1,576,280 | 1,296,533 | 1,584,673 | 1,531,867 | 1,576,280 |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area FEs | No | No | No | No | Yes | Yes | Yes | Yes |
| Worker Characteristics | No | No | No | No | Yes | Yes | Yes | Yes |
| Worker FEs | No | No | No | No | No | No | No | No |

Note: dependent variable is log real weekly wage. Worker characteristics include age, age squared and dummies for occupation groups, working part time and working in the public sector. Standard errors are clustered at the worker level and reported in parentheses. */**/*** denotes significance at the 10/5/1% level respectively.

Table 14: Weekly Wage Regressions with Worker Fixed Effects by Decade

| | (1) 1980s | (2) 1990s | (3) 2000s | (4) 2010s | (5) 1980s | (6) 1990s | (7) 2000s | (8) 2010s |
|---|---|---|---|---|---|---|---|---|
| Auto manuf. | 0.209*** | 0.283*** | 0.367*** | 0.424*** | 0.090*** | 0.079*** | 0.125*** | 0.151*** |
| | (0.008) | (0.009) | (0.011) | (0.013) | (0.010) | (0.010) | (0.018) | (0.019) |
| Manuf. | 0.196*** | 0.227*** | 0.258*** | 0.288*** | 0.079*** | 0.076*** | 0.092*** | 0.085*** |
| | (0.002) | (0.003) | (0.003) | (0.004) | (0.002) | (0.002) | (0.003) | (0.004) |
| N obs. | 1,237,024 | 1,528,321 | 1,480,848 | 1,520,217 | 1,237,024 | 1,528,321 | 1,480,848 | 1,520,217 |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area FEs | No | No | No | No | Yes | Yes | Yes | Yes |
| Worker Characteristics | No | No | No | No | Yes | Yes | Yes | Yes |
| Worker FEs | No | No | No | No | Yes | Yes | Yes | Yes |

Note: dependent variable is log real weekly wage. Worker characteristics include age, age squared and dummies for occupation groups, working part time and working in the public sector. Standard errors are clustered at the worker level and reported in parentheses. */**/*** denotes significance at the 10/5/1% level respectively.

Table 15: Mean Weekly Wage Firm Fixed Effects by Sector

| | Raw | | Controls | |
|---|---|---|---|---|
| | All | Emp. $\geq$ 100 | All | Emp. $\geq$ 100 |
| Non-manuf. | -0.06 | -0.06 | -0.02 | -0.03 |
| Manuf. | 0.34 | 0.35 | 0.15 | 0.15 |
| Autos | 0.70 | 0.67 | 0.34 | 0.30 |
| Autos - Manuf. | 0.36 | 0.32 | 0.18 | 0.16 |

Note: table shows mean firm fixed effects from a regression of log weekly wages by sector, weighted by employment.

Table 16: Auto Wage Premium Decomposition Underlying Regression Results

| | (1) | (4) |
|---|---|---|
| | 1980s | 2010s |
| Log(VA/Emp) | 0.271*** | 0.180*** |
| | (0.011) | (0.018) |
| Log(VA/Emp)*Auto | -0.029 | -0.0440* |
| | (0.029) | (0.024) |
| Constant | -0.852*** | -0.704*** |
| | (0.033) | (0.068) |
| N obs. | 105,271 | 46,618 |
| N firms | 22,373 | 12,962 |

Note: standard errors in parentheses clustered at the firm level. */**/*** denotes significance at the 10/5/1% level respectively.

Table 17: Auto Wage Premium Decomposition Alternative Parameterisation

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Portion due to differences in | | |
| | $\bar{w}^a - \bar{w}^{a'}$ | Productivity | Bargaining | N |
| 1980s | 0.15 | -0.04 | -0.09 | 105,271 |
| 2010s | 0.47 | 0.11 | -0.17 | 46,618 |
| Change | 0.32 | 0.15 | -0.08 | 151,889 |

Note: column (1) shows the difference in log average wages between auto manufacturers and other manufacturers, defined as gross wages per employee. Columns (2)-(3) show the estimated components of equation 8. Column (4) shows the sample size used to calculate the wage difference and estimate the components.