Investigating productivity-compensation decoupling across industries and income levels from 1997-2019.

Introduction

From 1997 to 2010, gross median hourly earnings and labour productivity grew in tandem. Since 2010, however, the growth of both variables has diverged.

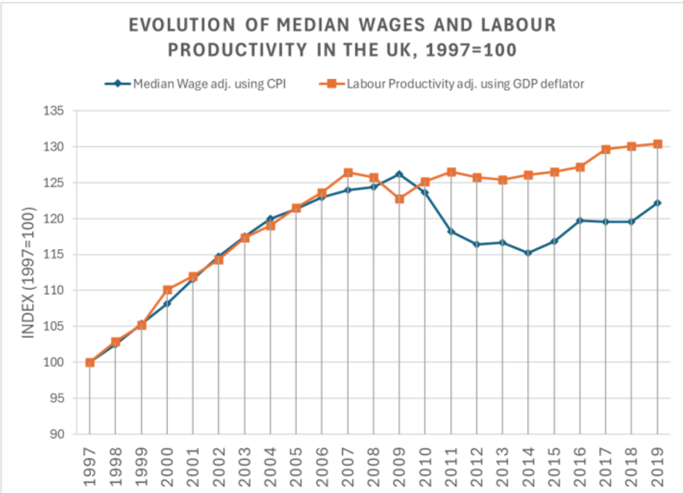


Figure 1

Over the period 1997-2010, median compensation and productivity each grew roughly 25% in real terms; since 2010, median compensation decreased by 1.2% while productivity grew by a further 4.22%. Combining these results, we see that over 1997-2019, compensation grew by 22.15% whereas productivity grew by 30.42%.

Stansbury & Summers (2018, p. 4), in their analysis of 'delinkage' in the US, make a critical point – just as correlation does not imply causation, two series appearing to decorrelate, as they do in figure 1, does not necessarily imply a causal break: there may be orthogonal factors lowering wages, even while increases in productivity act to raise them. This point has been disputed – regarding decoupling in the US, Bivens & Mishel (2015) write, "… productivity still managed to rise substantially in recent decades. But essentially none of this productivity growth flowed back into the paycheques of typical American workers." In the UK, Teichgraber and Van Reenen (2021) suggest that "the decoupling of productivity and median wages means the typical worker may not feel much benefit."

The debate is an important one, especially when the connection between productivity and living standards is often taken as a stylised fact, notably by Krugman (1990, p. xx) in his popular remark:

> "Productivity isn't everything, but, in the long run, it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker."

Investigating Stansbury & Summer's (2018) argument is complicated by the fact that what exactly is meant by "decoupling" or "delinkage" is not yet fully established. Some define decoupling as solely a divergence between the *median* compensation and mean productivity growth rates (Bivens & Mishel, 2015), while others suggest nuance to differentiate between mean and median compensation decoupling (Pessoa & Van Reenen, 2013; Stansbury & Summers, 2018; Ciarli, Salgado, & Savona, 2018; Ciarli, Di Ubaldo, & Savona, 2021); still other parts of the literature argue that decoupling should only be seen as a persistent fall in labour's share of income (Feldstein, 2008; Brill et al., 2017), where:

$$Labour\ share = \frac{Employee\ compensation + Self\ Employed\ Labour\ Income}{Gross\ Domestic\ Product - (Taxes - Subsidies)}$$

This final definition of decoupling is what led the ONS (2024) to state that "the UK has not experienced the decoupling between pay and productivity reported in other advanced countries". Indeed, the labour share of income in the UK has actually risen in recent years, shown in figure 2, contrary to what one might first think from figure 1.

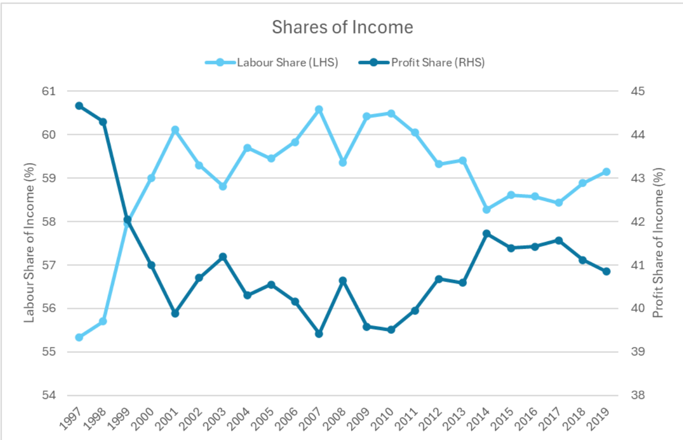


Figure 2

If we are concerned solely with the labour share, the productivity-compensation question is analysed only in the context of the production process. However, if we are concerned also with the typical worker's purchasing power, the question extends to encompass both production and consumption, because an increase in consumer prices can decrease real labour income, notwithstanding a decrease in the labour share. Figure 3 shows that the prices producers receive – and can thus pass on to workers – have grown slower in the service and manufacturing sector than consumer/retailer prices, implying that even if firms' revenues were shared with employees in constant proportion, the real value of that share could be declining.

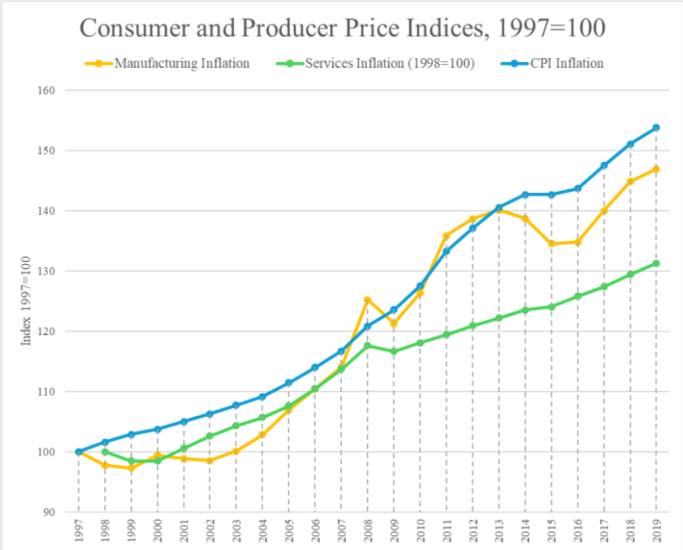


Figure 3

Furthermore, distinguishing between the 'typical', i.e., median, rather than the 'average', i.e., mean, worker allows broader statements to be made on how productivity translates to living standards in an environment where income inequality has risen – see figure 4 – and thus improvements to average compensation may have less of a connection with the typical employee as is often thought.

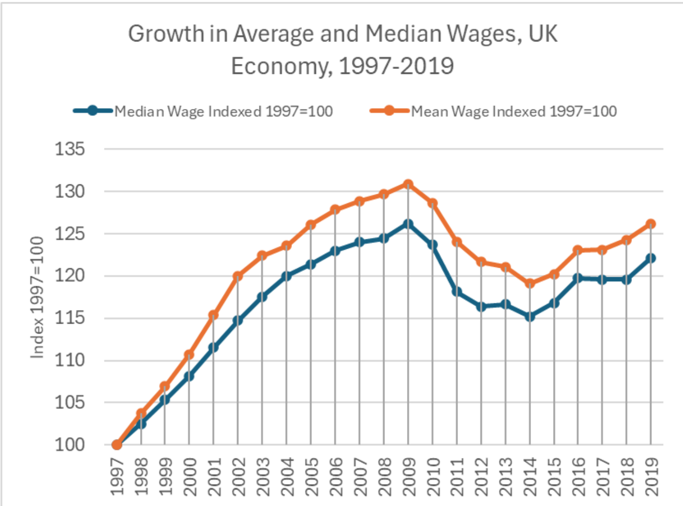


Figure 4

For these reasons, this paper will follow the terminology of Pessoa & Van Reenen (2013) and Teichgraber & Van Reenen (2021), by using 'gross' and 'net' decoupling to refer to the two different phenomena, where net decoupling refers to changes in the labour share, while gross decoupling refers to a divergence between median wages and average labour productivity, the former adjusted using consumer prices.

This paper will build primarily on work by Stansbury & Summers (2018) and Pasimeni (2018) by applying their methodology to the UK. Stansbury & Summers (2018) measured the elasticity of productivity on mean, median and 'production/non-supervisory' compensation in the US, while Pasimeni (2018) investigates only mean compensation in a panel of mostly EU member states. In order to analyse both types of decoupling and to fully assess Krugman's (1990) famous remark, this paper will focus primarily on median but also mean incomes, ignoring production/non-supervisory income as there is no dedicated dataset for this in the UK and because median income provides a clearer indicator of typical income. Contributions by Pessoa & Van Reenen (2013), Ciarli, Salgado & Savona (2018), Brocek (2019), Ciarli, Di Ubaldo & Savona (2021), Teichgraber & Van Reenen (2021) and Nasir et al. (2022) constitute the primary knowledge base of the status of the productivity-compensation nexus in the UK. As in Brocek (2019), this paper will further extend the analysis by examining the elasticity of productivity on not only median wages, but also across different wage percentiles and across different sectors; furthermore, this paper will build on Brocek (2019) by implementing previously key robustness checks and by further synthesising Brocek's (2019) methodology with Stansbury & Summers (2018). This paper concludes by finding a strong effect of productivity on both median and mean wages, indistinguishable from 1-to-1, across a range of specifications; to finalise, we analyse the technological change hypothesis for why the two metrics have diverged.

Previous Literature

The existing body of literature in the UK can be roughly grouped into two separate sections, broadly speaking, those which deal with quantitative regression analyses and those that deal with qualitative decoupling analyses. This section will analyse the benefits and drawbacks of each paper and conclude by explaining where new contributions can be made by implementing novelties from Stansbury & Summers (2018).

Ciarli, Salgado & Savona (2018) investigate how low-wage workers benefit from productivity growth in the UK; by using matched employer-employee combinations, they study effects of productivity at the firm, industry, and local labour market level. They find that, in the period 2011-2015, a 1% labour productivity (LP) increase led to an insignificant, 0.151%, and 0.225% increase in median wages at the firm, industry, and local labour market levels, respectively. For all wage percentiles below the median, a 1% LP increase led to either insignificant or negative wage changes at all levels – except in the lowest percentile at the firm level, where a 0.01% increase was identified. These findings are mirrored by Ciarli, Di Ubaldo & Savona (2021) who investigate the productivity-compensation nexus in London, Slough & Heathrow, and the rest of Great Britain at the local labour market level in the period 2004-2014; they found that a £1 increase in productivity led to a £0.35 and £0.26 increase in median wages in local labour markets across a 5-year and 10-year time horizon, respectively. While the use of absolute rather than relative measures is slightly opaque, the authors maintain that these findings signify gross decoupling.

Both papers paint a dismal picture of the state of gross decoupling in the UK but there are significant methodological improvements which could be made to paint a more accurate picture. First, as Ciarli, Salgado & Savona (2018, p. 15) point out, their findings reflect contemporaneous changes in wages due to productivity, and thus cannot capture lagged effects of productivity; these effects, however, are important – the authors themselves state that firms may postpone wage increase to gain a competitive advantage or to recover from losses, and Stansbury & Summers (2018) point out that lagged effects may exist because firms take time to discern to what extent increases in output are due to labour productivity. This problem remains unaddressed in Ciarli, Di Ubaldi & Savona (2021).

Pessoa & Van Reenen (2013) and Teichgraber & Van Reenen (2021) investigate changes to both net and gross decoupling. Net decoupling, ND, is equivalent to a decline in the labour share, and can be measured as the difference between labour productivity and *mean compensation* where both are adjusted by an output price deflator; gross decoupling, GD, which is depicted in figure 1, is defined as the difference between productivity and *median wages*, deflated by an output and consumer price deflator, respectively. The difference between the two measures can be decomposed to:

$$GD - ND = Inequality + Wage\ wedge + Price\ Wedge$$

Where $inequality$ represents differences between mean and median wages, $wage\ wedge$ represents differences between wages and total compensation per hour, and $price\ wedge$ represents differences between producer/output and consumer/retailer prices. Both papers argue that a rise in inequality and a shift in the composition of compensation toward non-wage benefits, such as pension contributions, are the predominant drivers of gross decoupling; the impact of differences in output and consumer price deflators is found to be very little – see figure 5.

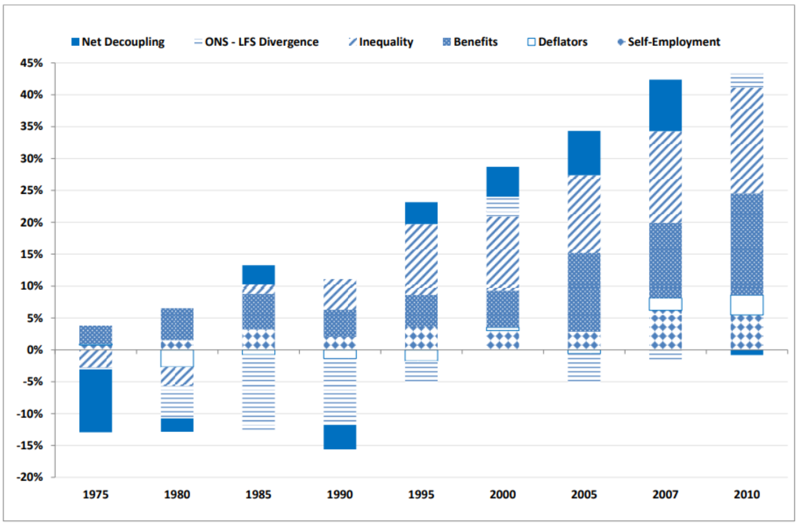


Figure 5 – source: Teichgraber & Van Reenen (2021, p. 18). Decoupling decomposition in the UK.

The complication, however, is that while this qualitative analysis of the productivity-compensation gap is interesting insofar as we can clearly visualise and decompose the decoupling, it lacks the quantitative statistical analysis to inform us of whether the productivity-compensation causal link is broken or simply decorrelated due to orthogonal factors.

Nasir et al. (2022) utilise a NARDL model to estimate the effects of a 1% rise in LP on real average weekly wages in the UK. The first paper to research the asymmetrical effects of productivity on wages, they find that, in the short run, a +1% productivity shock leads to a +1.105% wage increase; surprisingly, they also find that a -1% productivity shock leads to a +0.513% wage increase – again in the short run. Contemporary effects of productivity on wages are insignificant, supporting the hypothesis that it is necessary to include lags to capture the full effects of productivity. In the long run, a +1% productivity shock leads to a +2.416% increase in wages and a -1% productivity shock leads to a +1.123% increase in wages. Both short- and long-run results clearly suggesting strong wage downward stickiness. Control variables used in the study include inflation, GDP growth, and unemployment. These variables are theoretically understood to impact wages via competitive dynamics, efficiency or fair wages à la Stiglitz & Shapiro (1984) or Akerlof & Yellen (1990), or inflationary expectations. In the long run, these controls are not found to have any significant effect and productivity is left the sole determinant of wages; however, this link is not sufficient to contradict Pessoa & Van Reenen’s (2013) findings – as is claimed – or Teichgraber & Van Reenen's (2021) conclusion that gross decoupling has increased, given that Nasir et al. (2022) do not investigate median wage growth.

Finally, Stansbury & Summers (2018) provide, in this paper’s opinion, the best methodology to properly unite concerns raised by rising inequality, delayed productivity-compensation gains, and qualitative-quantitative analytic disparities. First, Stansbury & Summers (2018) find elasticities for the median, mean, and ‘production/non-supervisory’ wages in the US as 0.7-1 for the former two, and 0.4-0.7 for the final. Analysing all three variables allows the effects of inequality to be better captured via the difference between these coefficients. Second, to account for lagged effects, Stansbury & Summers (2018) use moving-averages – something which Pasimeni (2018) and Brocek (2019) also do.

While Brocek (2019) provides the clearest example of how to transition Stansbury & Summers’ (2018) regression model to the UK, there are a number of novelties which could further improve the analysis. First, Stansbury & Summers (2018) distinguish between gross and net productivity, where the latter reflects deductions made to GDP after subtracting capital depreciation – see figure 6.

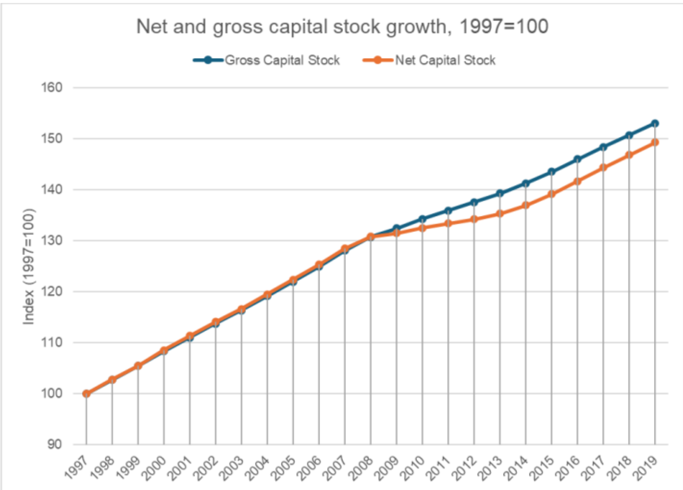


Figure 6

Because net domestic product (NDP) more accurately reflects the value of goods and services in an economy available for consumption (ONS, 2023), using it as the basis for productivity means we are better capturing what income is available to be split between labour and profit. Second, Stansbury &

Summers (2018) restrict unemployment data to the rate for 25-54 year-olds to avoid capturing demographic shift effects. Finally, as well as using moving averages, the Stansbury & Summers (2018) also use an ARDL model, further modifying time horizons.

By implementing these improvements, this paper will build on previous literature in the UK and more fully answer the question of how, precisely, productivity growth leads to changes in income and living standards.

Commented [DT1]: Mention difference in wages and compensation

Methodology and Results

As stated, we will regress a plethora of different models, investigating the effects of productivity on both average and median wages. The variable term $wages$ and productivity ($prod$) will be a catch-all for both kinds and nuance will be introduced when results are presented.

We first estimate a simple model, regressing real median wages on real productivity – logs are used to estimate elasticities rather than absolute units:

$$\log wages_t = \beta_0 + \beta_1 \log prod_t + \epsilon_t$$

We control for unemployment as in Stansbury & Summers (2018) because unemployment is likely to affect bargaining dynamics à la the *efficiency wages* theory of Stiglitz & Shapiro (1984) wherein higher unemployment increases employee's opportunity cost of being fired for substandard performance; furthermore, it likely affects compensation in the short-run, because high unemployment is associated with an economic downturn, where pay rises will be rare regardless of productivity changes. This gives us:

$$\log wages_t = \beta_0 + \beta_1 \log prod_t + \beta_2 unemp_t + \beta_3 unemp_{t-1} + \epsilon_t$$

Finally, we account for lagged effects; this is done by regressing using three-year moving averages rather than simply contemporaneous t-time variables:

$$\frac{1}{3}\sum_{0}^{2} \log wages_{t-i} = \beta_0 + \beta_1 \frac{1}{3}\sum_{0}^{2} \log prod_{t-i} + \beta_2 \frac{1}{3}\sum_{0}^{2} unemp_{t-i} + \beta_3 \frac{1}{3}\sum_{0}^{2} unemp_{t-i-1} + \epsilon_t$$

Data

Data used is provided primarily by the Office for National Statistics (ONS), although some data is also taken from the Bank of England's "A millennium of macroeconomic data" dataset. All presented data has been logged to reduce variance and is plotted on a natural log scale.

Median wages from 1987 can be found for the entire population, although they are given as *median gross weekly earnings* (ONS, 2023); for hourly rates, data is only available from 1997 (ONS, 2024). Alternatively, an index of real average labour compensation (adjusted with a consumption deflator) is available from 1971 (ONS, 2025). While Pessoa & Van Reenen (2013) and Stansbury & Summers (2018) are correct to point out the important difference between gross wage and total compensation, median compensation in the UK is not available; as such, the median earnings-productivity coefficient will be underestimated. It is likely not a level effect: non-wage benefits have been growing as a percent of the total pay packet (Pessoa & Van Reenen, 2013; Teichgraber & Van Reenen, 2021); as a result, this will likely skew regression results. See figure 7 for a visual comparison between the three different measurements.

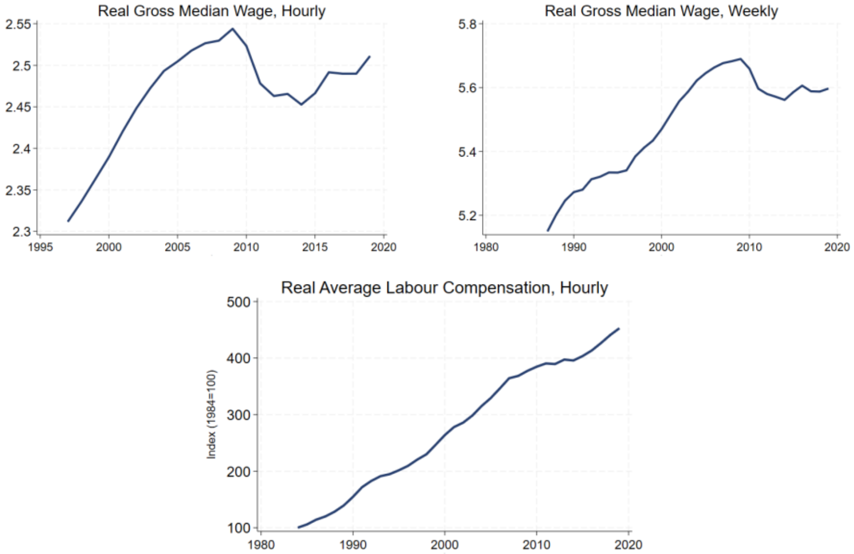


Figure 7

Labour productivity is available from 1760 (Bank of England, 2024), although this is calculated using annual GDP rather than Net Domestic Product (NDP), or value added (either gross or net) – the latter of which is common in some modern ONS publications (ONS, 2022). Data on productivity hours worked is available as an index since 1971 (ONS, 2025) and this is combined with GDP, NDP, GVA and NVA data to find values for productivity – see figure 8.

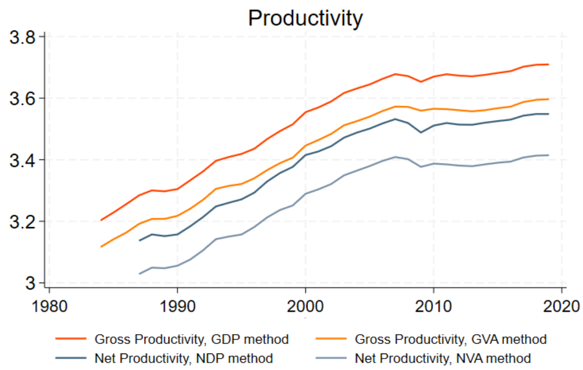


Figure 8

Finally, unemployment figures are available from 1855. To avoid capturing effects from demographic shifts, unemployment data from the 25-49 year-old age range is used to check for robustness – this data is only provided from 1997 onwards, however – see figure 9.

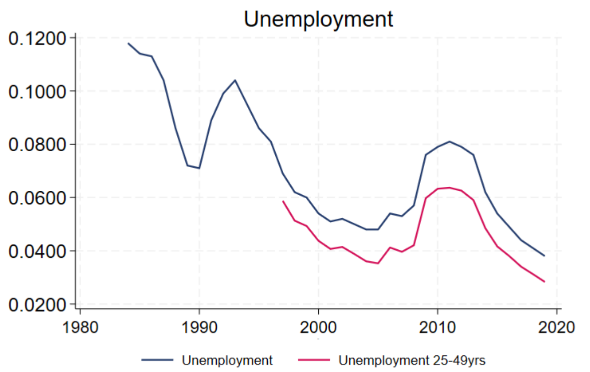


Figure 9

Robustness checks will be performed in the Alternative Specifications section.

Baseline Specification

The baseline regression will use data available from 1987 onward:

Variable Name	Description
$wages$	Gross weekly median wages
$prod$	Net Domestic Product per annual hours worked
$unemp$	Unemployment rate, 16yr+

To account for cases where weekly earnings increase in cases where hours worked increase rather than real pay per hour increasing, we control for hours worked ($hours$) in our model:

$$\frac{1}{3}\sum_{0}^{2} \log wages_{t-i}$$
$$= \beta_0 + \beta_1 \frac{1}{3}\sum_{0}^{2} \log prod_{t-i} + \beta_2 \frac{1}{3}\sum_{0}^{2} unemp_{t-i} + \beta_3 \frac{1}{3}\sum_{0}^{2} unemp_{t-i-1}$$
$$+ \beta_4 \frac{1}{3}\sum_{0}^{2} \log hours_{t-i} + \epsilon_t$$

The final step is to test for stationarity. Because Brocek (2018) and Nasir et al. (2022) find structural break-points in their earnings data, a direct Augmented Dickey-Fuller (ADF) test is rejected in favour of a unit root test accounting for a single structural break when examining $wages$. All other variables except $wages$ are investigated for stationarity using an ADF test. They are fitted to the equation:

$$\Delta x_t = \beta_1 x_{t-1} + \sum_{0}^{i} \Delta x_{t-i} + [\lambda t, \alpha, \beta_0]$$

Where x is replaced with a given variable and i is the number of lags needed to eliminate autocorrelation according to the Breusch-Godfrey test; see Appendix x for how this was calculated for each variable. The array $[\lambda t, \alpha, \beta_0]$ represents possible alternative specifications of the ADF test which are implemented if the variable exhibits trending, drifting, or non-zero mean behaviour.

Table A – ADF test results

Variables	i	MacKinnon Approximate p-value		
		With λt	With α	With β_0
At Level				
$\boldsymbol{prod}$	1	0.9808	0.0323**	0.3208
$\boldsymbol{unemp}$	1	0.0836	0.0136**	0.1666
$\boldsymbol{hours}$	1	0.0850	0.3011	0.8867
First Difference				
$\boldsymbol{prod}$	0	0.0068***	0.0007***	0.0078***
$\boldsymbol{unemp}$	0	0.1152	0.0020***	0.0260***
$\boldsymbol{hours}$	2	0.0013***	0.0001***	0.0003***
Null Hypotheses				
		H_0: Random walk with or without drift	H_0: Random walk with drift	H_0: Random walk without drift

[*,**,***] indicate rejection at the [1%,5%,10%] significance level.

We find that most non-differenced variables are therefore $I(1)$. $\Delta unemp$ cannot reject the null that it is a random walk with or without drift and is therefore also investigated for evidence of structural breaks.

The Clemente-Montañés-Reyes (CMR) test on STATA (Baum, 2018) uses the Perron (1992) methodology and critical values to test for the presence of a single structural break and a unit root. These tests determine break points endogenously and thus let the data speak for itself. Results for order of integration of weekly earnings data are somewhat inconclusive at the 5% level however expanding the margin of significance to 10% and referring back to the data offers clarity. Table A presents the CMR test results with the structural break identified. IO and AO stand for Innovative Outlier and Additive Outlier, respectively. The IO model is used when the structural break is assumed to take place gradually, the AO model when the break takes place instantaneously (Perron & Vogelsang, 1992, pp. 303-304); they therefore generate different estimates for when structural breaking occurs. These test statistics are significant if the null hypothesis of a unit root is rejected.

Table B – CMR test results for general wages and unemployment

Variables	CMR Test Statistic (IO)	CMR Test Statistic (AO)	Break-Date (IO/AO)
$\boldsymbol{wage}$	-3.331	-3.149	1995 / 2000
$\boldsymbol{unemp}$	-3.645	-4.267***	1995 / 1999
$\boldsymbol{\Delta wage}$	-3.548	-3.484*	2008 / 2007
$\boldsymbol{\Delta unemp}$	-3.772	-4.144***	2008 / 2007
***Critical Values* (Perron & Vogelsang, 1992, pp. 307-308)**			
10%	-3.86	-3.22	
5%	-4.27	-3.56	
1%	-4.62	-3.89	

[*,**,***] indicate rejection at the [1%,5%,10%] significance level.

$wage$ cannot reject the null of a unit root at a 95% confidence level. This is likely a result of lack of observations, rather than an indicator that $wage$ is $I(2)$. To test this, the number of observations is increased by delineating weekly earnings into adult male and adult female categories to allow observations from 1970-2019[1]. ADF test results for male and female earnings are shown in Table C.

Table C – ADF test results for male and female wages

Variables	i	MacKinnon Approximate p-values		
		With λt	With α	With β_0
At Level				
$\boldsymbol{wage_{male}}$	0	0.9737	0.0198**	0.2377
$\boldsymbol{wage_{female}}$	0	0.9606	0.0011***	0.0181**
First Difference				
$\boldsymbol{wage_{male}}$	0	0.0000***	0.0000***	0.0000***
$\boldsymbol{wage_{female}}$	0	0.0000***	0.0000***	0.0000***
Null Hypotheses				
		H_0: Random walk with or without drift	H_0: Random walk with drift	H_0: Random walk without drift

[*,**,***] indicate rejection of null at the [1%,5%,10%] significance level.

We find that adult male and female wages show highly statistically significant stationarity when differenced once, in all scenarios. This suggests that general earnings stationarity would be more conventionally significant given more observations. We therefore take $\Delta wages$ and $\Delta unemp$ as stationary with a structural break during 2007 (the AO break-date is preferred because a sudden structural break more accurately reflects the 2007 financial crisis which is almost certainly what is being captured by the estimated break date). As Brocek (2018) notes, this implies that relationships found between wage growth and other variables will be weaker in post-crisis years – an alternate specification could be devised to break in 2007, however lack of observations on either side of the break-point would probably skew coefficients towards insignificance or spurious significance.

We therefore regress in first differences across 1987-2019 using the following baseline specification:

$$\frac{1}{3}\sum_{0}^{2} \Delta \log wages_{t-i}$$
$$= \beta_0 + \beta_1 \frac{1}{3}\sum_{0}^{2} \Delta \log prod_{t-i} + \beta_2 \frac{1}{3}\sum_{0}^{2} \Delta unemp_{t-i} + \beta_3 \frac{1}{3}\sum_{0}^{2} \Delta unemp_{t-i-1}$$
$$+ \beta_4 \frac{1}{3}\sum_{0}^{2} \Delta \log hours_{t-i} + \epsilon_t$$

Alternative Specifications

Alternative specifications will extend the analysis, such as regressing using *average compensation* rather than *median earnings*; this allows us to factor in previously unavailable data viz. the wage wedge, at the same time obscuring the effects of inequality. At the same time, these alternative specifications – as well as the baseline – will be subject to robustness checks. Rather than using new models, robustness checks will typically consist of the substitution of variable data for alternative data that accounts for certain problems raised in the literature, e.g., using the 25-49yr old unemployment range to discount effects of demographic shift, or using *hourly* median earnings data,

[1] Prior to 1985, population-wide median earnings are not available. Instead, only data for adult males (21+) and adult females (18+) are available and a synthetic median is difficult to generate due to the heterogeneity of the definition of 'adult'.

which is only available from 1997. New specifications and robustness checks are formalised in table *x*.

Specification	$wage$	$prod$	$unemp$	$hours$	*Extra variables*
Baseline	Median weekly earnings	Net Domestic Product per hour	16+ unemployment rate	Hours worked across the whole economy	N/A
A1	Average hourly compensation	As above	As above	Not included	N/A
A2	As above	As above	As above	As above	Year-on-year inflation rate introduced as control variable (Nasir et al., 2022).
A3	10^{th}-90^{th} percentiles, gross hourly earnings, 1997-2019.	As above	As above	As above	N/A
R1	-	Net Value Added per hour	-	-	-
R2	-	Gross Domestic Product per hour	-	-	-
R3	-	Gross Value Added per hour	-	-	-
R4	-	-	25-49yr old unemployment rate	-	-
R5	-	-	-	-	Model estimated as ARDL rather than with Moving Averages

'Baseline' represents the baseline specification, A1-3 represent two additional alternative specifications, and R1-5 represent robustness checks that will be run on *all specifications*.

Baseline Results

Table D – Baseline regression results

Regressand: $\Delta wages$

Variable	β Coefficient	Robust Std. Error	p-value	95% Confidence Interval	
$\Delta prod$	1.1300***	0.3473	0.003	[0.4172,	1.8425]
$\Delta unemp$	1.1015	1.3500	0.422	[-1.6686,	3.8716]
$\Delta L.unemp$	-2.2055**	0.7495	0.007	[-3.7434,	-0.6676]
$\Delta hours$	0.1633	0.5266	0.759	[-0.9173,	1.2439]
Model Characteristics:					
R^2	0.5260				
$Adj.R^2$	0.4558				

[*,**,***] indicate rejection of null at the [1%,5%,10%] significance level.

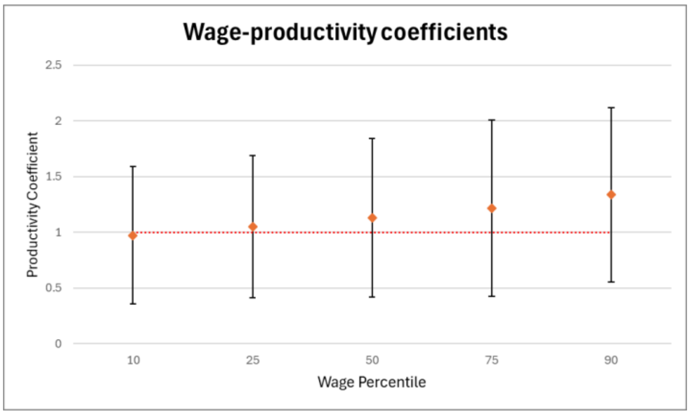
As in Stansbury & Summers (2018) we find that the marginal effect of productivity growth on median wage growth is statistically significant, and not significantly different from one-to-one. We continue the estimation for the 10th, 25th, 75th and 90th income percentiles; only $prod$ coefficients are shown here, see Appendix x for further results.

Table E – Wage percentile regression results by percentile

Regressand	$\Delta prod$ Coefficient	Robust Std. Error	p-value	95% Confidence Interval	
$\Delta wage_{10}$	0.9720***	0.3008	0.003	[0.3547,	1.5891]
$\Delta wage_{25}$	1.0486***	0.3105	0.002	[0.4115,	1.6857]
$\Delta wage_{75}$	1.2154***	0.3848	0.004	[0.4259,	2.0050]
$\Delta wage_{90}$	1.3350***	0.3811	0.002	[0.5530,	2.1170]

[*,**,***] indicate rejection of null at the [1%,5%,10%] significance level.

These results are formalised in Figure z.



Figre *z* –

All results pass through the dashed red line, indicating that, at the 95% confidence level, none of the coefficients are indistinguishable from a one-to-one relationship.

Alternative Specifications

Table F – Baseline regression results for A1				
		Regressand: $\Delta comp$		
Variable	**β Coefficient**	**Robust Std. Error**	**p-value**	**95% Confidence Interval**
$\Delta prod$	1.1760***	0.2380	0.000	[0.6886, 1.6634]
$\Delta unemp$	3.0202***	0.9218	0.003	[1.1319, 4.9085]
$\Delta L.unemp$	-3.3289***	0.8631	0.001	[-5.0968, -1.5610]
Model Characteristics:				
R^2	0.5770			
[*,**,***] indicate rejection of null at the [1%,5%,10%] significance level.				

Table G – Baseline regression results for A2				
		Regressand: $\Delta comp$		
Variable	**β Coefficient**	**Robust Std. Error**	**p-value**	**95% Confidence Interval**
$\Delta prod$	1.3610***	0.1757	0.000	[1.0000, 1.7222]
$\Delta unemp$	2.9824***	1.0069	0.006	[0.9127, 5.0520]
$\Delta L.unemp$	-2.9954***	0.9124	0.003	[-4.8708, -1.1200]
Δinf	0.6602*	0.3791	0.093	[-0.1190, 1.4394]
Model Characteristics:				
R^2	0.6609			
[*,**,***] indicate rejection of null at the [1%,5%,10%] significance level.				

Tables F and G show the relationship average total labour compensation growth and productivity growth. Controlling for inflation strongly reduces the standard deviation of the $prod$ coefficient; we find that average labour compensation has a much stronger relationship with productivity than median earnings – this difference captures the effects of inequality and the wage wedge. These results are shown in figure p.

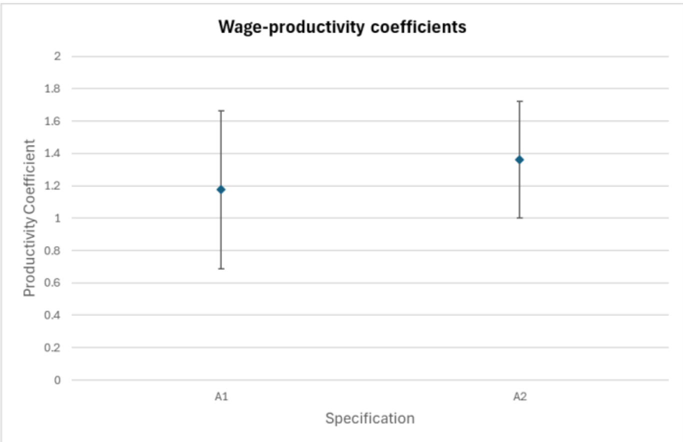


Figure p

Table H – Median regression results for A3				
		Regressand: $\Delta comp$		
Variable	**β Coefficient**	**Robust Std. Error**	**p-value**	**95% Confidence Interval**
$\Delta prod$	0.9840***	0.1898	0.000	[0.5852, 1.3829]
$\Delta unemp$	-0.3691	0.5302	0.495	[-1.4829, 0.7447]
$\Delta L.unemp$	-0.4100	0.4667	0.391	[-1.3904, -0.5705]
Model Characteristics:				
R^2	0.7240			

[*,**,***] indicate rejection of null at the [1%,5%,10%] significance level.

Table I – All wage percentiles' productivity coefficients A3				
Regressand	**$\Delta prod$ Coefficient**	**Robust Std. Error**	**p-value**	**95% Confidence Interval**
$\Delta wage_{10}$	0.8208***	0.2093	0.001	[0.3811, 1.2605]
$\Delta wage_{20}$	0.7768***	0.1765	0.000	[0.4059, 1.1477]
$\Delta wage_{30}$	0.9103***	0.1736	0.000	[0.5455, 1.2751]
$\Delta wage_{40}$	0.9648***	0.1833	0.000	[0.5797, 1.3499]
$\Delta wage_{50}$	0.9840***	0.1898	0.000	[0.5852, 1.3829]
$\Delta wage_{60}$	1.0685***	0.1926	0.000	[0.6639, 1.4732]
$\Delta wage_{70}$	1.1699***	0.1953	0.000	[0.7595, 1.5802]
$\Delta wage_{80}$	1.2255***	0.1973	0.000	[0.8109, 1.6400]
$\Delta wage_{90}$	1.3018***	0.2003	0.000	[0.8810, 1.7226]

[*,**,***] indicate rejection of null at the [1%,5%,10%] significance level.

Figures from Table I are shown in figure *y*:

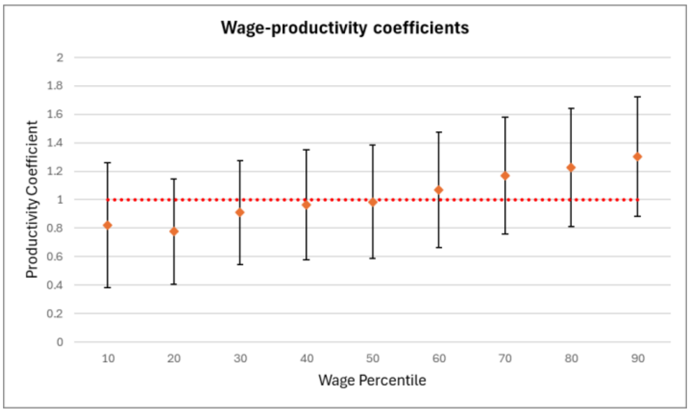


Figure *y*

Again, the relationship identified in Stansbury & Summers (2018) are supported – across all wage percentiles, a one-to-one relationship between wage growth and productivity growth cannot be rejected at the 95% level.

Robustness checks R1-5 do not meaningfully affect productivity coefficients – see Appendix y for results.

Discussion

Conclusion and Policy Implications