Investigating productivity-compensation decoupling across income levels from 1987-2019.

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.

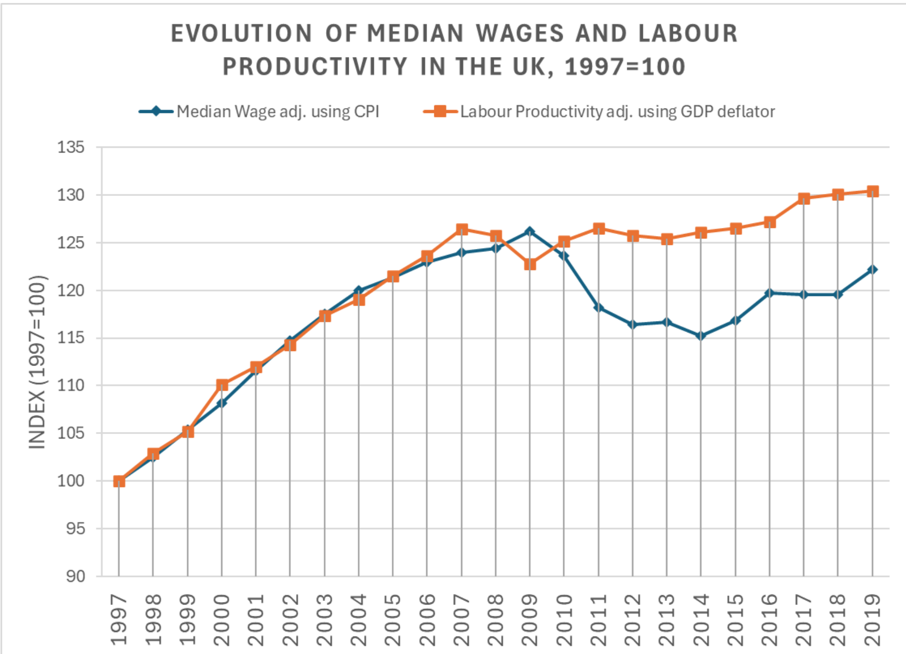

Figure 1

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.

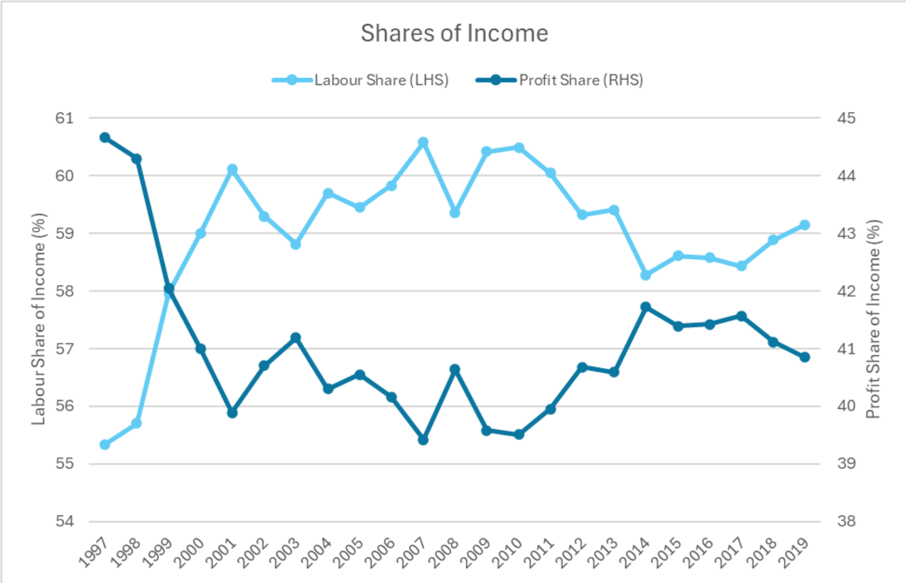

Figure 2

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.

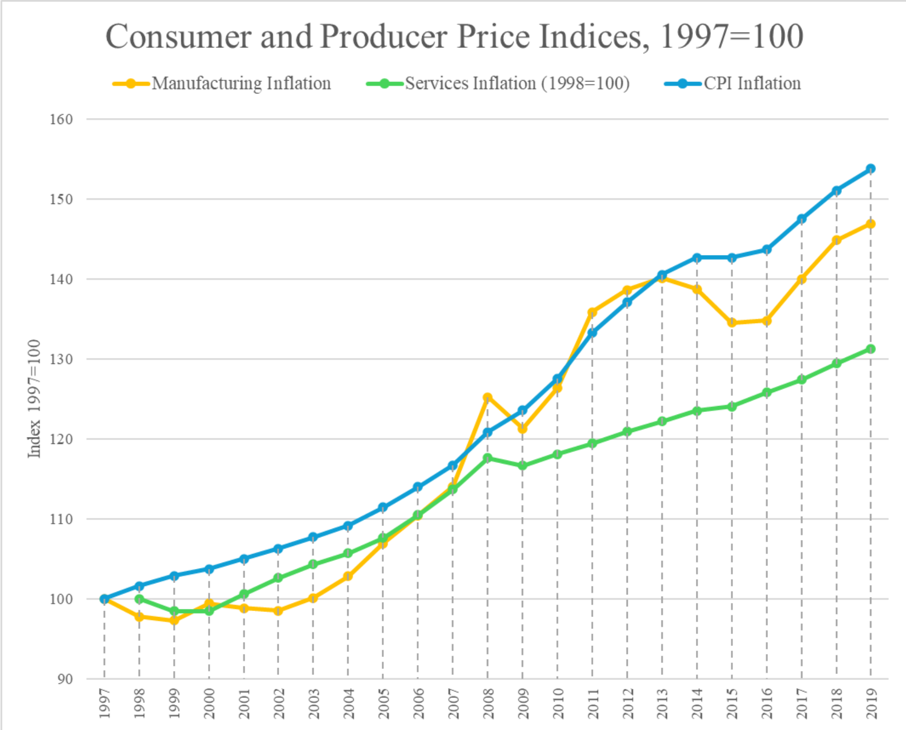

Figure 3

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 growth in average compensation may have less of a connection with living standards, and the typical employee, as is often thought.

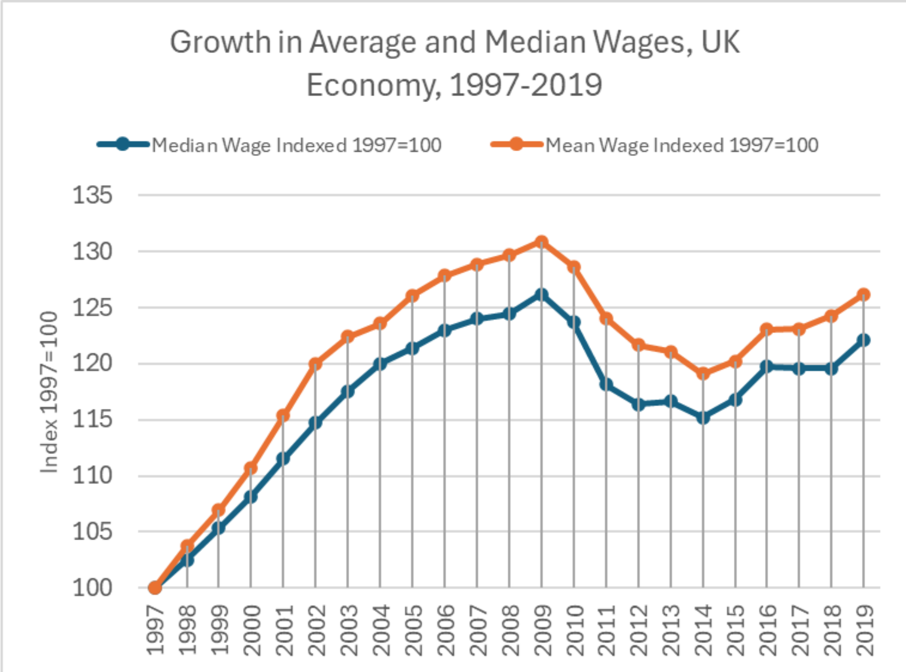

Figure 4

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 average incomes as there is no dedicated dataset for this in the UK and because median income provides a clearer indicator of living standards. 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 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 explore the policy implications of these findings.

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.

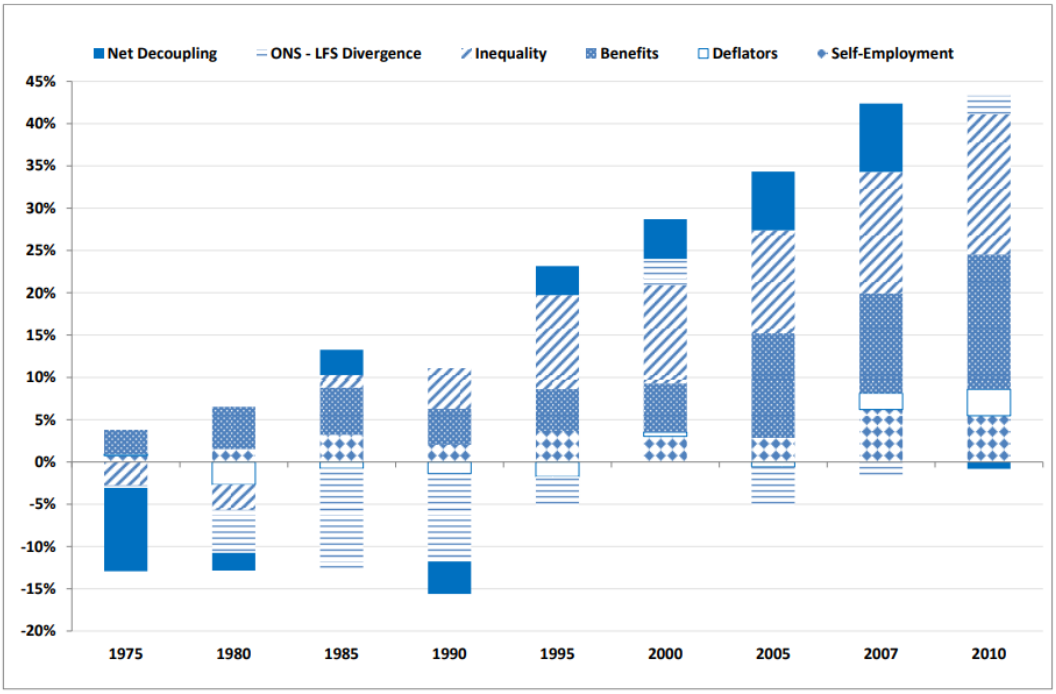

Figure 5 – source: Teichgraber & Van Reenen (2021, p. 18). Decoupling decomposition in the UK.

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 visually diverging 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.

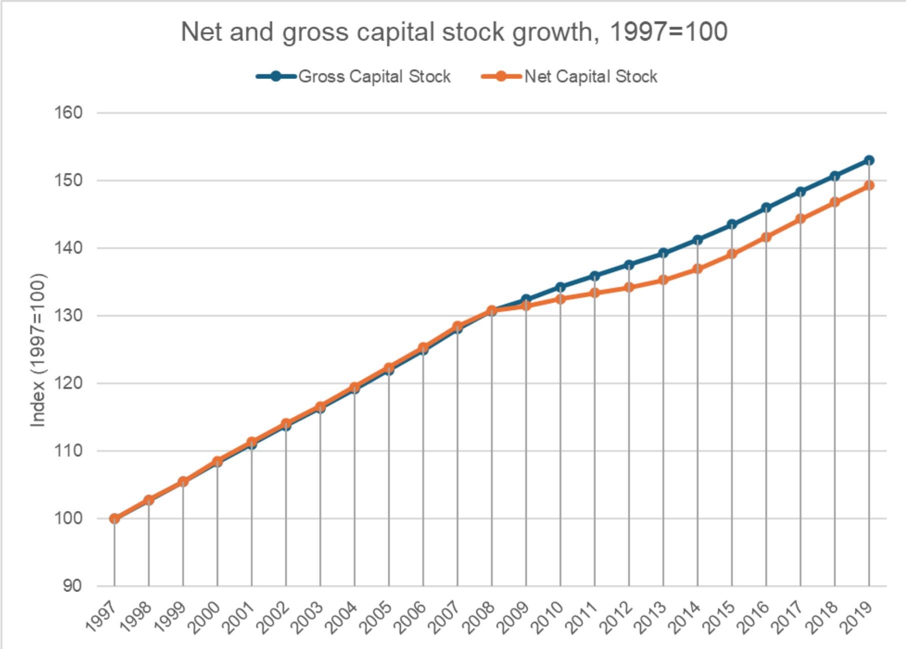

Figure 6

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 wages 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, and check time-horizons beyond their baseline three-year moving average.

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.

Empirical Strategy

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 then 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.

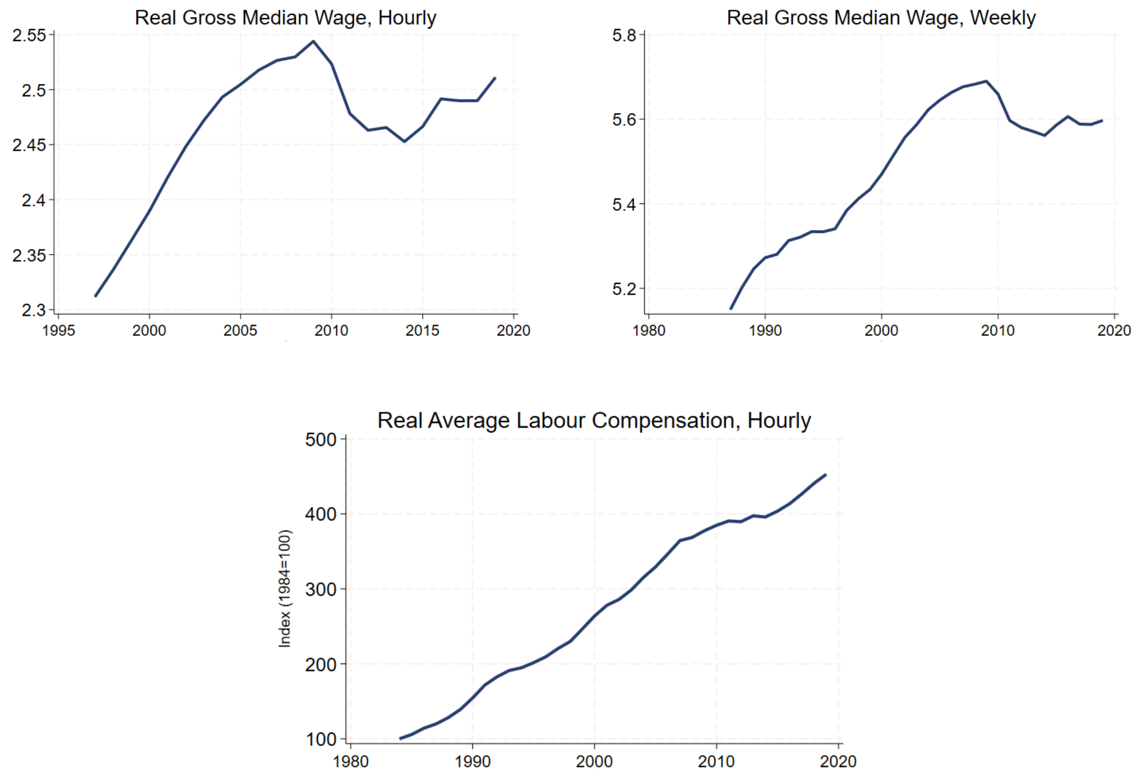

Figure 7

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) – value-added productivity measurements 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.

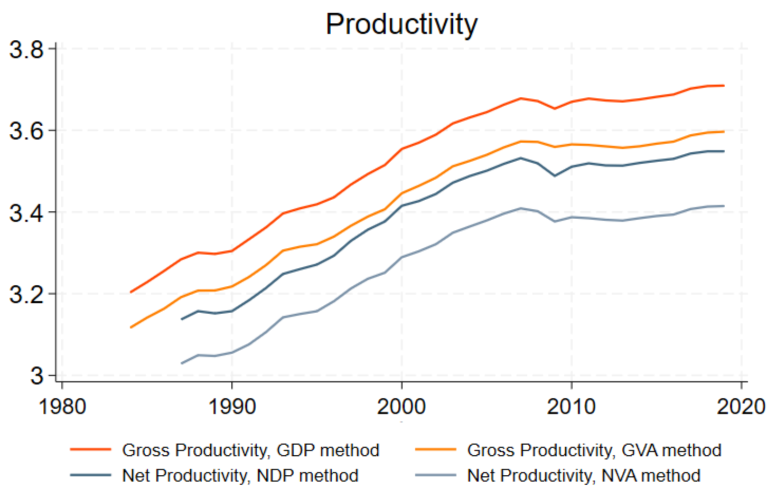

Figure 8

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.

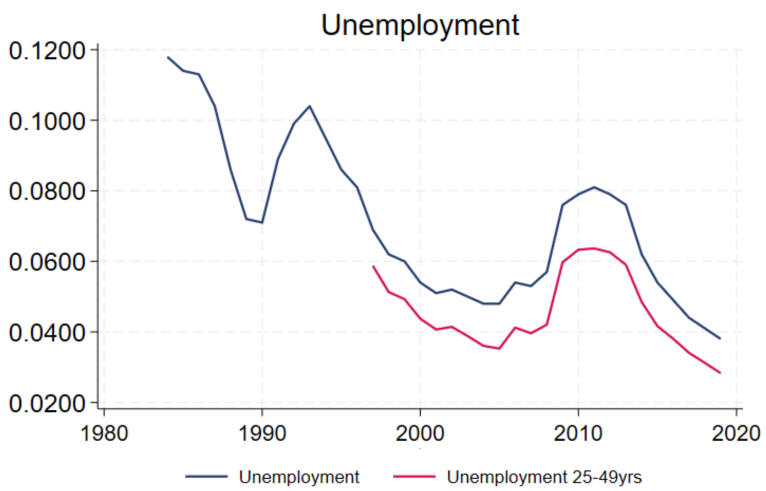

Figure 9

Robustness checks are outlined in the **Alternative Specifications** section.

Baseline Specification

The baseline regression will use data available from 1987 onward:

Variable Name	Description
$\boldsymbol{wages}$	Gross weekly median wages
$\boldsymbol{prod}$	Net Domestic Product per annual hours worked
$\boldsymbol{unemp}$	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 (2019) 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	$\boldsymbol{i}$	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.

$\Delta wage$ 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 likely what is 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:

[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'.

$$\frac{1}{3}\sum_{0}^{2} \Delta \log wages_{t-i}$$

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

$$+ \beta_4 \frac{1}{3}\sum_{0}^{2} \Delta \log hours_{t-i} + \epsilon_t$$

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. These alternative specifications – as well as the baseline – will also 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, which is only available from 1997. New specifications and robustness checks are formalised in table *x*.

Specifi-cation	$wage$	$prod$	$unemp$	$hours$	*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, renamed *comp*	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*.

Results

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 full regression results.

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]

Table E – Wage percentile regression results by percentile

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

These results are formalised in Figure z.

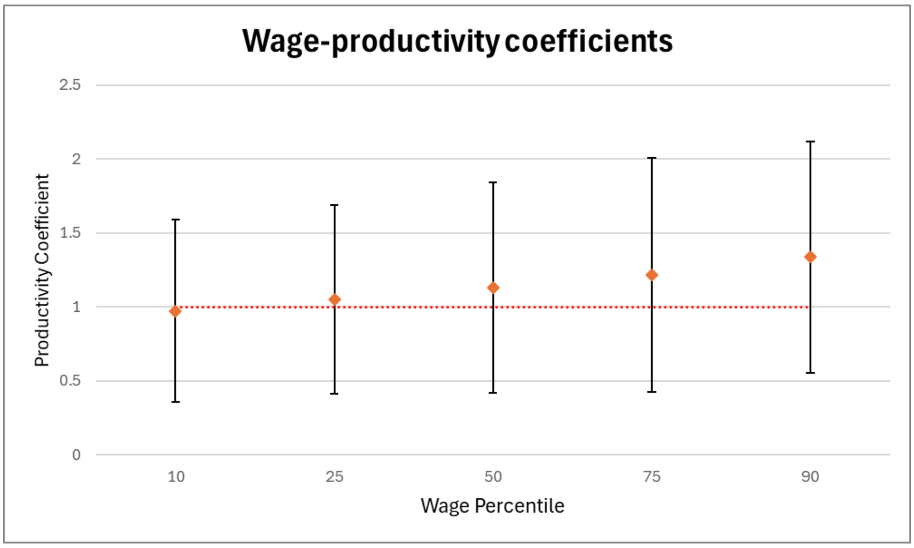

Figure *z* –

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.

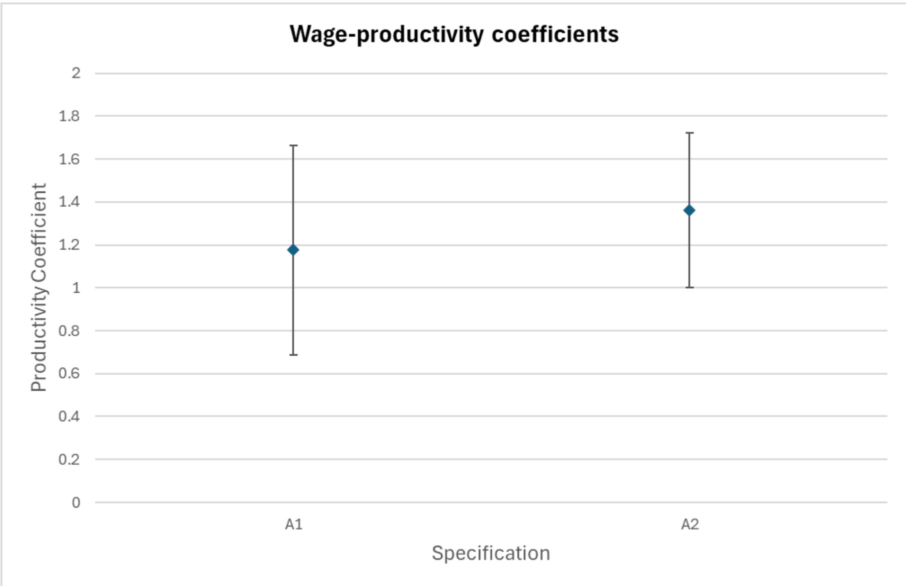

Figure p

Table H – Median regression results for A3					
		Regressand: $\Delta wages$			
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*:

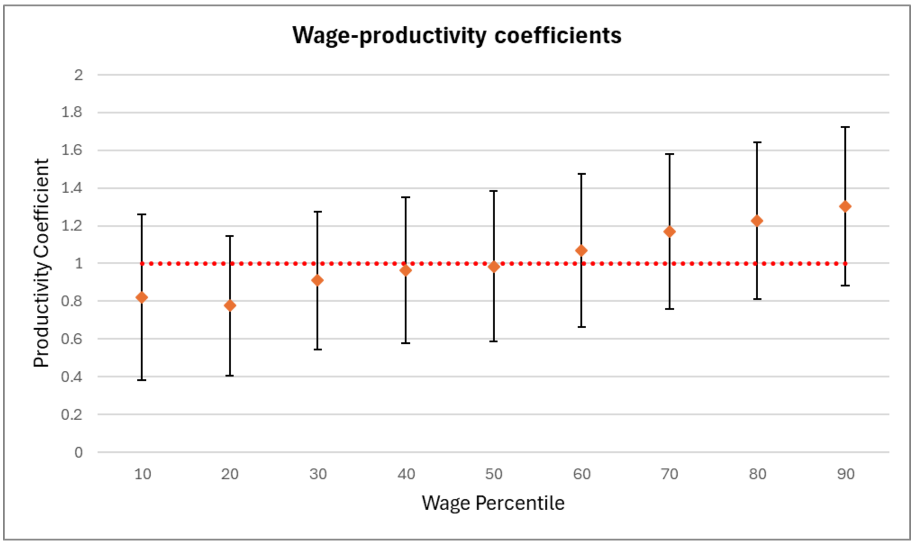

Figure *y*

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 and Policy Implications

The regression results in Tables D-I show that there is strong correlation between wage growth, both average and median, and productivity growth in the UK. While these are only short-run estimates, the results do largely still support Krugman's assertion that productivity is key factor which must grow to raise living standards. The evidence does not support the conclusions found in Ciarli, Salgado & Savona (2018) or Ciarli, Di Ubaldo & Savona (2021), where a statistically insignificant, or sometimes negative, elasticity between earnings and productivity is estimated. Instead, coefficient estimates are broadly in line with figures found in Stansbury and Summers (2018) and Brocek (2019). The best explanation for the discrepancy between findings is likely the inclusion of lagged effects; the conclusion that there exists only a "feeble link", and that we must "enlarge the policy perspective beyond productivity" is therefore called into. However, it is clear that there must be some broader policy prescriptions set out besides raising productivity given that there remain orthogonal factors to wages and productivity which cause visible divergence even while not impacting statistical correlation. What exactly these "orthogonal factors" are is not yet fully settled – Stansbury & Summers (2018) suggest a few competing hypotheses, such as technological progress, education and skills, globalisation, or the broad decline of worker power; Nasir et al. (2022) suggest that this characteristic lack of worker bargaining power is the best explanation for slow wage growth in the retail sector; Pasimeni (2018, p. 19) also furthers the bargaining power hypothesis, arguing that unemployment elasticities can be used as a proxy to capture changing labour bargaining power à la the efficiency wages hypothesis of Stiglitz & Shapiro (1984) – the negative, lagged, significant unemployment elasticity found the baseline regression supports this idea. Combining these theories and the collected evidence, it should be clear that while productivity is probably the most important factor which needs to rise to increase earnings and living standards, full employment must also be closely targeted to ensure gains from productivity are not lost due to low bargaining power. Bargaining power can also be increased via greater unionisation, although trade-off effects of unionisation on productivity should be considered – for the UK, Barth, Bryson, & Dale-Olson (2017) find a positive correlation between union density and productivity, whereas Doucouliagos & Laroche's (2003) meta-analysis finds a negative association.

Productivity elasticity estimates diverge from Brocek (2019) when considering the distribution other than at the median; we find the top 10% of wage earners have the largest productivity elasticity, whereas Brocek (2019) suggests that effects are greatest, on average, at the median. Our study therefore suggests that while labour productivity growth does benefit all wage-earners, top earners enjoy higher associated levels of wage growth, on average; this suggestion is further supported by the fact that the productivity elasticity of *average* total labour compensation is 1.3610 using specification A2, higher than the median earnings coefficient of 1.1300. The difference suggests strong inequality effects – it is true that the difference between 'average compensation' and 'median earnings' captures both the inequality *and* wage wedge, however Pessoa & Van Reenen (2013) and Teichgraber & Van Reenen (2021) point out that non-wage benefits themselves are likelier to accrue amongst top-earners.

One possible explanation that has not been adequately investigated yet in the literature is the heterogeneity of labour productivity. While Gabaix et al. (2016) do novel modelling work on accounting for certain high-performing firms and managers, little has been done on simpler regressions where, rather than analysing *average* labour productivity, the labour productivity distribution is divided into percentiles/quartiles to allow for like-for-like regressions with earnings strata. This would shed light on the extent that the discrepancy between median earnings and average labour productivity is caused by, for instance, low working bargaining power allowing the transfer of labour income into shareholder profit, versus the possibility that labour productivity is unequally distributed, with earnings reflecting that distribution. The former case suggests that the government should focus on greater average labour productivity and ‘recoupling’ policies, such as stronger labour institutions; the latter suggests that the prior approach is inadequate and that stronger redistribution is necessary to ease income inequality, as ‘recoupling’ will simply mirror unequal labour productivity distribution into unequal income distribution.

Among the other control variables introduced, one-period lagged unemployment also has a significant marginal effect in the baseline specification, indicating that there is a strong time-lag component for wages to adjust following unemployment shocks. In alternative specifications, it is estimated that contemporaneous positive shocks to unemployment likely increase wages, while past unemployment shocks tend to decrease wages to a greater extent than the shock initially increased them. Therefore, while this study does not fully clarify the relationship, the general conclusion that unemployment has a significant negative effect on wage growth still holds and the bargaining-power hypothesis is still supported by the evidence; full employment targeting remains a clear policy implication.

Inflation is another control variable, introduced only in the A2 alternative specification to replicate Nasir et al.’s (2022) model. No statistically significant effects are found – this casts doubt on conflict theories of inflation, which posit inflation as the result of wage-price or price-wage second-round effects (Rowthorn, 1977; Blanchard, 2022; Rowthorn, 2024). However, there is reason to believe that insignificant coefficients in this case do not imply conflict theories are incorrect. First, the stated aim of many central banks, such as the Bank of England, is to keep inflation at or near 2%; if central banks are successful in their objective, then no wage-price or price-wage spirals should emerge, and we therefore cannot differentiate in this study between a successful BoE policy regime successfully suppressing real conflict-driven inflation, versus an insignificant BoE policy regime in a world where conflict theories of inflation simply do not hold. Second, conflict theories require, as a prerequisite for inflation, some conflict. As Rowthorn (2024) points out, there is little worker bargaining power in the UK, and as such mark-ups are more easily maintained while real wages are more easily suppressed (this was most recently made clear in the COVID-19 pandemic, although this period is not analysed in the study); therefore, increased wage demands to pre-empt inflation do not materialise into increased wages, and we should expect an insignificant coefficient even allowing for a conflict-driven model of inflation, simply due to lack of conflict.

This new inflationary perspective complicates earlier policy prescriptions of full employment and potentially higher union membership: with higher bargaining power, conflict-driven inflation could become more prevalent. The key to tempering high wage demands driven by increased bargaining power seems to be the role of trust between capital owners and labour institutions (Blanchard, 2004). Fomenting this trust is hard, and strict oversight is needed between both parties – examples of failure include the 1977 Moncloa Pacts in Spain, where inflation fell rapidly following an agreement to freeze wages in return for a series of promised political reforms, such as property taxes, and new income tax-bands. Ultimately, these reforms were never carried out or implemented in such a way as to render them insignificant (Casanova & Andrés, 2014, p. 312). Events like these are inflection points which can slowly build trust or wipe away goodwill very quickly, and an important policy aim of the UK going forward must therefore be to balance greater labour-bargaining power and full employment policies with improved labour-capital relations, trust and strict oversight.

Conclusion

Income and productivity appeared to have decoupled in the UK following the Great Financial Crisis in 2007-8. Various tests performed on the median weekly earnings timeseries found a structural break in these two years. Due to the clear divergence between changes to productivity and earnings in this time period, a literature emerged questioning whether the established link between these two variables, exemplified most clearly in Krugman's (1990, p. xx) statement that productivity is, "in the long run, […] almost everything", was broken. This study finds that productivity and income, both median and average, have not decoupled or 'delinked' in the UK, even while visually diverging. Instead, this study finds that a 1% increase in average labour productivity will increase weekly gross median earnings by 1.13%, and total average labour compensation by 1.36%. The regressions are checked for robustness following recommendations from the existing literature, such as: focusing on net, rather than gross, product; using both a value-added and domestic product definition of productivity; using both weekly and hourly gross earnings; and finally, accounting for demographic changes partially reflected in the unemployment rate. None of these changes meaningfully affect the conclusion that the correlation between earnings and productivity found at the 95% confidence level is not statistically significantly different from one-to-one.

When our analysis is expanded to include more income percentiles, productivity is still a statistically significant determinant, however clear inequality effects are present. As seen in Figure *z*, all along the income distribution, the correlation between earnings and productivity is again not statistically significantly different from one-to-one, however, on average, benefits from an increase to the average labour productivity accrue to top earners. Whether this is due to uncompetitive distribution of quasi-rent, or simply a reflection of unequal labour productivity distribution, is still an open question. What is clear, is that improvements to average labour productivity benefit everyone, but benefit top earners more.

These findings reinforce the importance of increasing productivity in the policy debate, and cast doubt on prior suggestions to de-emphasise it in favour of redistributive policies. However, the clear visual divergence shown in Figure 1 cannot be ignored: there are certainly orthogonal factors which must be addressed to ensure gains from productivity are not lost. This study supports the bargaining-power hypothesis, wherein the UK's characteristically low union density means that workers likely find it harder to sustain wage increases from productivity. Indeed, a 1% increase in unemployment is associated with a 2.21% decrease in wages in the next year, indicating that falling bargaining-power certainly decreases wages.

Finally, these policy prescriptions must contend with the UK's relative success in avoiding wage-price or price-wage second-round effects, captured most clearly by an insignificant inflation coefficient in specification A2. Higher labour bargaining power may precipitate conflict-inflation if union density, for example, is not paired with increased trust between workers and capital owners. If workers can accept wage freezes, trusting that improved firm performance in later periods will lead to higher real wages, and if these promises are in fact delivered, conflict inflation can be avoided and living standards can be effectively raised.