Online addendum for the paper *"Class, Power, and the Structural Dependence Thesis: Distributive Conflict in the UK, 1892-2018"*

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Abstract

This online-only addendum contains some additional material related to the paper "Class, Power, and the Structural Dependence Thesis: Distributive Conflict in the UK, 1892-2018". Section 1 displays the short-run WSER cycles not shown in the paper. Section 2 describes the estimation methodology adopted in the paper. Section 3 presents the causality analysis of the Vector Error Correction Model (VECM). Section 4 compares our union density variable with various measures of collective bargaining coverage. Section 5 reports on the results obtained with different specifications of the VECM. Section 6 contains a description of trends in the functional distribution of income and WSER cycles focusing on manual production workers.

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1 Additional WSER cycles

This section provides the scatter plots of the short run WSER cycles describing deviations from trend values not included in section 4 of the paper. Figures A1 and A2 each display four additional clockwise cycles. As mentioned in the main paper there are five cycles that display anticlockwise patterns, displayed as Figure A3, and one, Figure A4, that has a pattern difficult to discern. Finally, Figure A5 portrays a clockwise but possibly incomplete cycle encompassing the last few years of our sample.

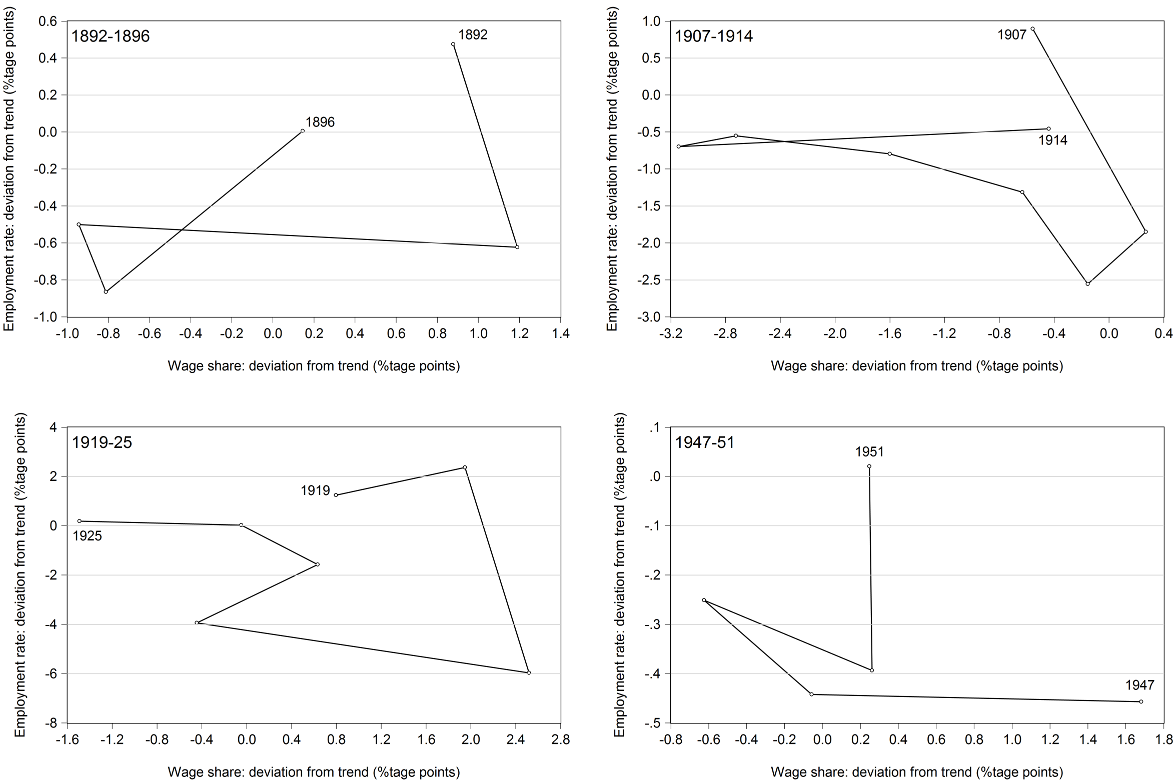


Figure A 1: *Four WSER Clockwise Cycles, UK, 1892-1951*

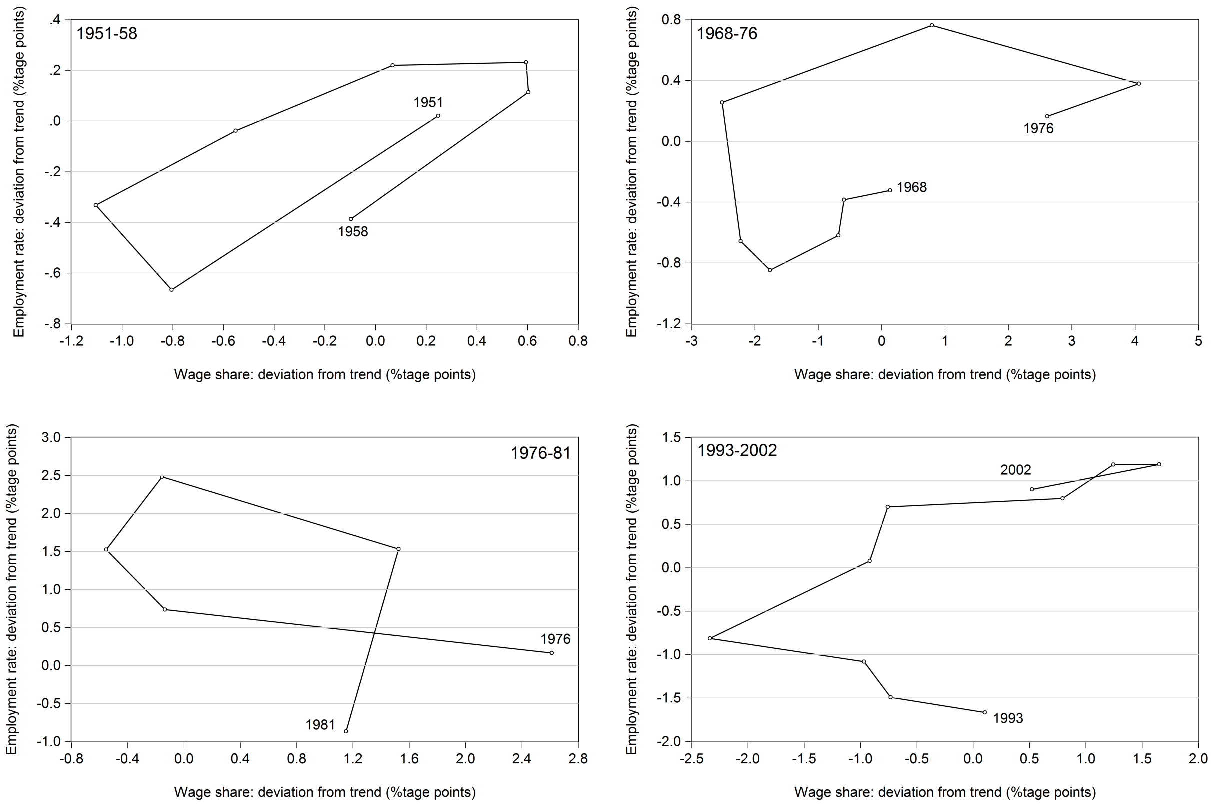


Figure A 2: *Four More WSER Clockwise Cycles, UK, 1951-2002*

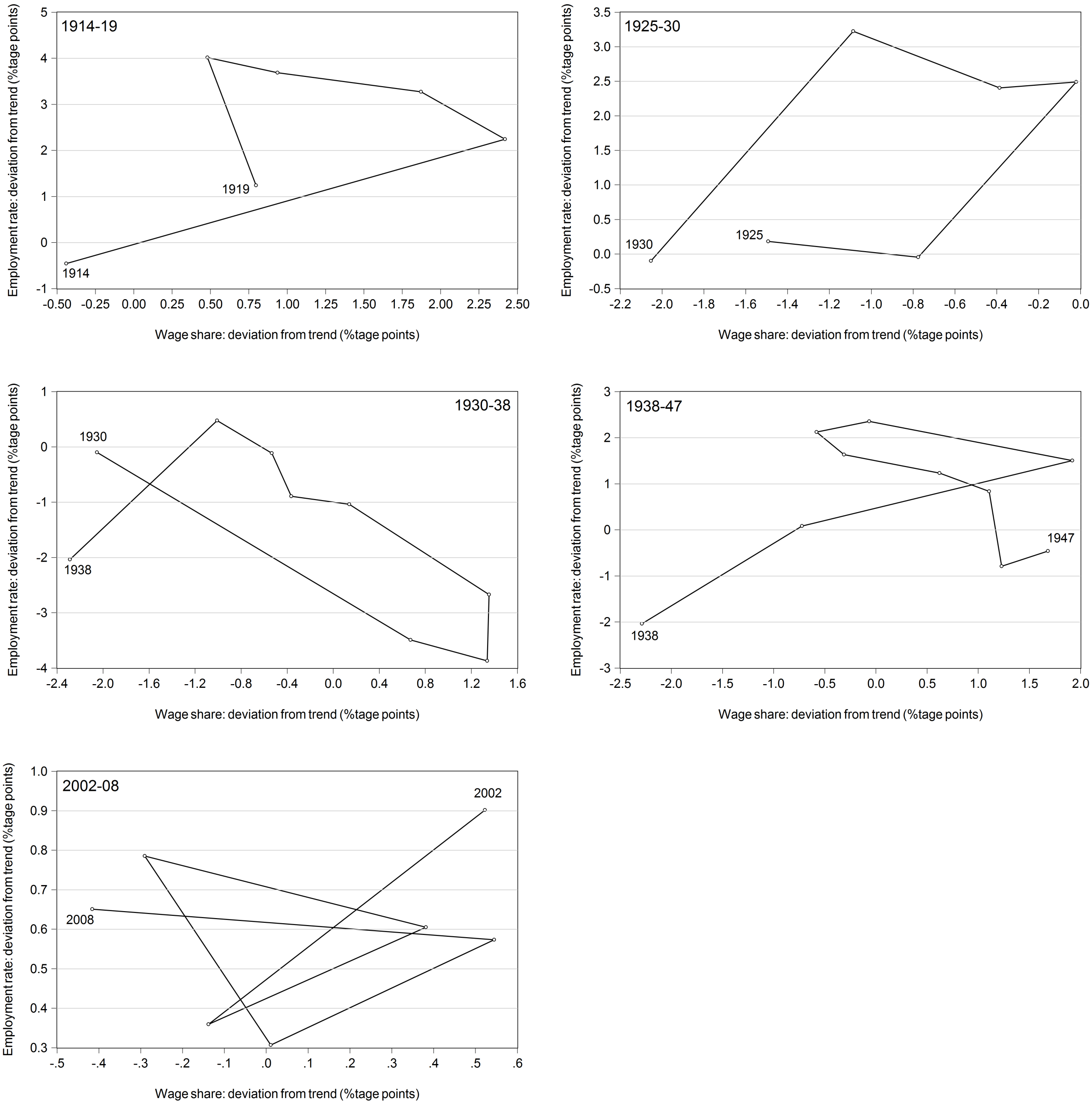


Figure A 3: *Five WSER Anti-Clockwise Cycles, UK, 1914-2008*

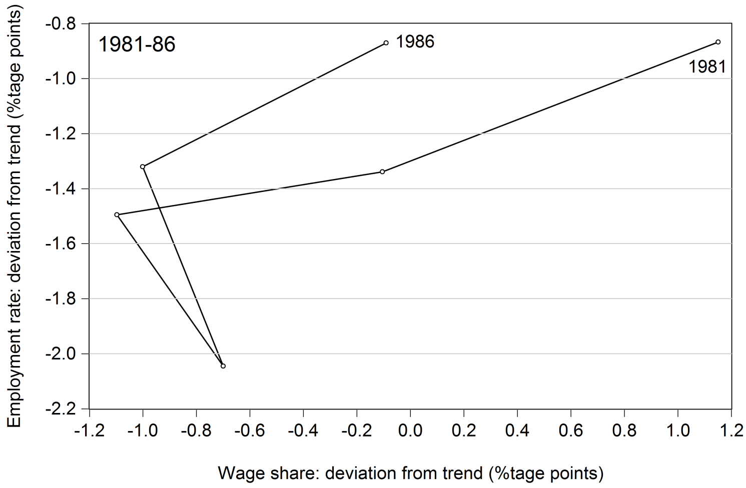


Figure A 4: *One Period With No Clear Cyclical Pattern, UK, 1981-86*

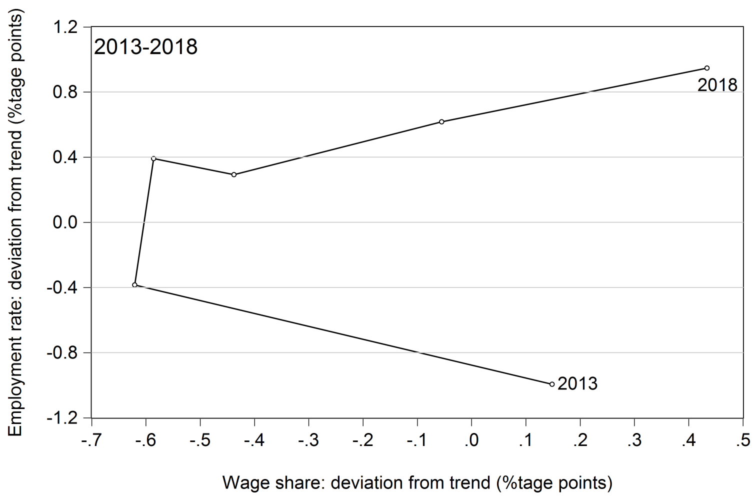


Figure A 5: *One Incomplete Clockwise Cycle, UK, 2013-2018*

2 Estimation of long-run relations: methodology

This section provides a general description of the econometric methodology adopted in the paper, mostly following Lütkepohl and Krätzig [4]. Consider a set of K time series variables, $y_t = (y_{1t}, ..., y_{Kt})'$. Using a vector auto-regressive approach (VAR), the dynamic interactions of the vector components are:

$$y_t = \sum_{j=1}^{p} \Phi_j y_{t-j} + v_t, \tag{1}$$

where $v_t = (v_{1t}, ..., v_{Kt})'$ is a sequence of independently and identically distributed shocks, with $E(v_t) = 0$, $E(v_t v_t') = \Omega$, with $rank(\Omega) = K$, p is the finite number of lags and the order of the VAR model, and Φ_j is a $K \times K$ matrix.

In general, a process such as (1) is stable if the polynomial defined by the determinant of the autoregressive operator has no roots in and on the complex unit circle, i.e. $\det(I_K - \sum_{j=1}^{p} \Phi_j z^p) \neq 0$ for $|z| \leq 1$, where I_K is the $K \times K$ identity matrix. On the assumption that it has initiated in the infinite past ($t = 0, \pm 1, \pm 2, ...$), it generates stationary time series that have time-invariant means, variances, and covariance structure. If the variables in y_t are integrated of order 1 ($I(1)$) the process is not stationary, but if they have a common stochastic trend so that there are linear combinations of them that are $I(0)$, they are cointegrated.

A convenient representation of (1) with cointegrated relations is the Vector Error Correction Model (VECM):

$$\Delta y_t = \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + \Pi y_{t-1} + v_t. \tag{2}$$

If the $VAR(p)$ process has unit roots, i.e. $\det(I_K - \sum_{j=1}^{p} \Phi_j z^p) = 0$ for $z = 1$, the matrix $\Pi = (I_K - \sum_{j=1}^{p} \Phi_j)$ is singular. If $rank(\Pi) = r$, then Π can be written as a product of $(K \times r)$ matrices A and B, with $rank(A) = rank(B) = r$ as follows: $\Pi = AB'$. In a VECM representation, long- and short-run dynamics are modelled separately and By_{t-1} expresses the effects of deviations from each long-run equilibrium. The matrices Γ_j express the short-term interactions among the variables of interest.

If the multivariate process y_t is not stationary, the shocks may also have permanent effects. Hence, there may be r nontrivial $1 \times K$ vectors β_i, $i = 1, ..., r$, such that $\beta_i' y_t$ is stationary for all i. In this case the deviations from the linear relation $\beta_i' y_t$ are only temporary, and $\beta_i' y_t$ is a stable relationship in the long-run. For all i, the variables in y_t with nonzero coefficients in $\beta_i' y_t$ are then cointegrated and β_i is the cointegrating vector and r is the cointegrating rank.

A stationary y_t can also be expressed in its Wold moving average representation, i.e. as a function of the original shocks v_t, $y_t = \sum_{j=0}^{\infty} \Psi_j v_{t-j}$where $\Psi_0 = I_K$ and

$$\Psi_s = \sum_{j=0}^{s} \Psi_{s-j} \Phi_j, \qquad s = 1, 2, ... \tag{3}$$

can be computed recursively from the reduced-form coefficients of the VAR in levels in (1). The coefficient of this representation can be interpreted as reflecting the responses to impulses hitting the system. The (i, j)th elements of the matrices Ψ_s trace out the expected response of $y_{i,t+s}$ to a unit change in y_{it} holding constant all past values of y_t. Since the change in y_{it} given its past is measured by the innovation v_{it}, the elements of Ψ_s represent the impulse responses of the components of y_t with respect to the v_t innovations. In the stationary case, $\Psi_s \to 0$ as $s \to \infty$, hence the effect of an impulse vanishes over time. When y_t is nonstationary the Ψ_s impulse response matrices can be computed in the same way as in (3) based on VARs with integrated variables, even though a Wold representation as such does not exist for nonstationary cointegrated processes. In this case the Ψ_s may not converge to zero as $s \to \infty$ and some shocks may have permanent effects. As the impulse responses have been criticized because underlying shocks are not likely to occur in isolation if the components of u_t are instantaneously correlated, orthogonal innovations are preferred by adopting a Choleski decomposition of the covariance matrix. As the ordering of the variables in the vector y_t may produce different shocks, we followed standard practice of trying various triangular orthogonalizations, checking the robustness of the results with respect to the ordering of the variables (Lütkepohl and Krätzig [4], p.167).

As in our analysis y_t is a $K \times 1$ vector, there may be only $r \leq (K-1)$ nontrivial cointegrating vectors, which can be stacked in a $r \times (K-1)$ cointegrating matrix B with cointegrating rank r. The cointegrating rank can be estimated using a likelihood-ratio test known as the trace test, whose null hypothesis is that there are no more than r cointegrating relations. The method starts by testing $r = 0$ and accepts as $\widehat{r}$ the first value of r for which the trace statistic fails to reject the null (Johansen [3]). Finding the r stable long-run relationships is of interest for the economic interpretation of SDT since they provide information concerning the determinants of long-run income distribution. But it is also important for statistical reasons, for when y_t is not stationary, the estimates of the VAR in (1) and of the IRF are consistent but less efficient, unless integration and cointegration are properly accounted for.

Given the cointegration rank r, simultaneous estimation of Γ_j, A and B can be obtained using the full information maximum likelihood framework (Johansen [3]).

3 Causality analysis

In this section, we provide the results of our Granger-causality analysis for the four key variables $\log GDP_t, u_t, e_t, w_t$ using our main model, that is, the VECM estimated in Table 3, Model 2 (with restrictions). According to Granger-causality, "variable x Granger-causes y" means that past values of x provide information that helps predict y above and beyond the information contained in past values of y alone.

Table 1, reporting standard χ-squared tests, suggests that the structure of causality goes from $\log GDP_t$ to all other variables, and from u_t and e_t to w_t, whereas w_t does not help predict any other variables, as shown by the Granger-causality scheme presented in Figure A6.

4 Collective bargaining coverage

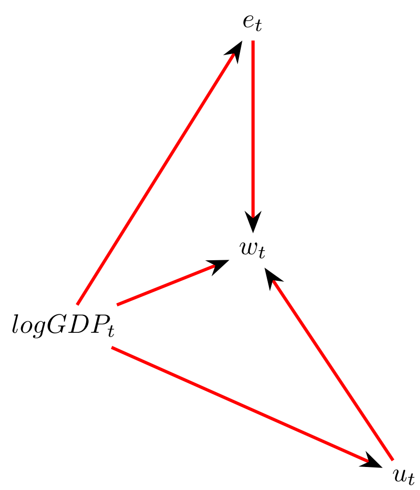
There exists no continuous, long-run series providing information on the coverage of collective pay-setting institutions in the United Kingdom. The OECD dataset starts in 1960 and annual data are available only from 1993. In his authoritative study, Milner [5] provided a set of estimates starting in 1895, but the reconstructed series has major gaps. Therefore we cannot estimate our VECM model using collective bargaining coverage as an alternative measure of workers' bargaining power. However, Figure A7 shows the time path of the two indices of the power resources of the working class.

Table A 1: Granger-causality analysis

Dependent variable: Δw_t			
Excluded	Chi-sq	df	Prob.
Δe_t	10.211	1	0.001
Δu_t	6.474	1	0.011
$\Delta logGDP_t$	5.856	1	0.016
All	12.644	3	0.006
Dependent variable: Δe_t			
Excluded	Chi-sq	df	Prob.
Δw_t	0.256	1	0.613
Δu_t	0.009	1	0.924
$\Delta logGDP_t$	5.355	1	0.021
All	8.742	3	0.033
Dependent variable: Δu_t			
Excluded	Chi-sq	df	Prob.
Δw_t	0.061	1	0.805
Δe_t	0.293	1	0.588
$\Delta logGDP_t$	18.599	1	0.000
All	33.817	3	0.000
Dependent variable: $\Delta logGDP_t$			
Excluded	Chi-sq	df	Prob.
Δw_t	3.305	1	0.069
Δe_t	0.326	1	0.568
Δu_t	0.034	1	0.854
All	3.676	3	0.299

Notes: Sample: 1892 2018. Included observations: 125

Figure A 6: Granger-causality scheme



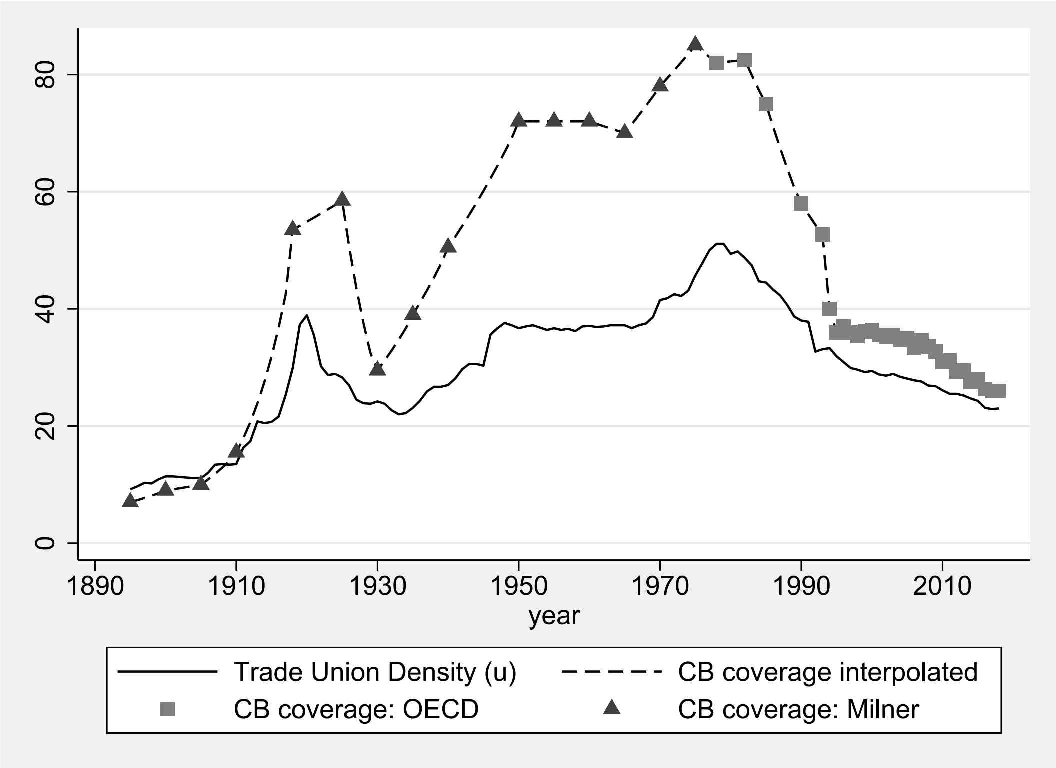


Figure A 7: Collective bargaining coverage and Union Density, UK, 1892-2018

The time series of the union density variable is the same as in the paper. The time series of the collective bargaining index is constructed as follows: from 1895 to 1975 we use the midpoint of Milner's [5] estimates of the coverage of collective pay-setting machinery in Britain; from 1975 onwards we use OECD data. The dashed line represents interpolated values for missing years. The correlation coefficient between union density and collective bargaining coverage thus constructed is 0.946. This result does not change if either the lower or the upper bound of Milner's estimates are used instead, or if one drops the interpolated values of the collective bargaining coverage index and measures the point correlation between the two variables: in all cases, the correlation coefficient is above 0.92.

Data on collective bargaining after 1960 can be found on the OECD website at

https://stats.oecd.org/Index.aspx?DataSetCode=CBC

5 Alternative specifications of the VECM model

We have run a host of different robustness checks on the main econometric model, testing – among other things – a set of different definitions of all variables. In this section we present in more detail *only* the results of the estimation of the most significant alternative specifications of the Vector Error Correction Model (VECM), which are summarized in section 6 of the paper. The other results are available from the authors upon request.

First, we estimated the VECM using an alternative measure of trade union density, namely the ratio of trade union membership as measured in the paper to total employment in heads plus claimant count unemployment, i.e. total labour force. Second, we estimated the model using an alternative measure of the employment rate as the ratio of employees in employment to the sum of total employment and claimant count unemployment. Third, we replaced $\log GDP$ with a measure of accumulation of capital, i.

We then estimated the VECM including various measures of the power resources of capitalists. Here we present the results of the model in which we replaced $\log GDP$ first with the log of total non-dwellings capital stock, $\log K$, and then with an openness index, k, capturing property income from overseas as a percentage of the sum of property income from overseas, total domestic profits, and an estimated profits component of mixed income.

In each of the robustness checks, our strategy has been to replace *one* variable at the time (either union density or the employment rate or $\log GDP$) and closely replicate – step by step – the estimation procedure of the VECM outlined in section 5 of the paper (see also section 2 above). In this section, for each of the robustness checks, we present only the estimated VECM and the Impulse Response Functions (IRFs). Details of the results of all other tests (the modified Dickey–Fuller t test, the Schwarz's Bayesian information criterion, and so on) underlying the estimates below are available from the authors upon request.

Concerning data sources for the robustness checks in this section, the time series data are for the whole UK economy. Apart from data on trade union membership and claimant count unemployment, all time series data are taken from Thomas and Dimsdale [6]. Claimant count unemployment data for 1971-2018 are electronically available from the Office for National Statistics at http://www.ons.gov.uk/ (each series has a 4 digit identifier, as listed below). Prior to 1971 they are taken from Hills et al [2]. The main series are described in Appendix A of the paper. Therefore here we only describe data sources for the additional variables.

In Table A2:

Trade union density is the ratio of trade union membership as measured in the paper to total employment in heads (Worksheet A50, column B) plus Claimant Count unemployment (ONS, Series BCJD for 1971-2018, and prior to 1971 Worksheet 22, column O from Hills et al [2].

In Table A3:

The employment rate is [Total employment in heads (Worksheet A50, column B, updated by ONS Series MGRZ) less Self-employment (Worksheet A50, column D), updated by ONS Series MGRQ] divided by [Total employment in heads (as above) plus Claimant Count unemployment (as above)]

In Table A5:

Total nominal non-dwellings capital stock is taken from Worksheet A55, column V. Then natural logs are taken.

In Table A4:

The variable i is the growth rate of total nominal non-dwellings capital stock as constructed in Table A5.

In Table A6:

Investment income inflows to total property income:

(i) Investment income inflows to the UK from 1946-2018 are from ONS HMBN. Data from 1892-1946 is from Thomas and Dimsdale [6] Worksheet A36, Column X. These latter are adjusted by splicing backwards from 1946 using the 1946 ratio of ONS to Thomas and Dimsdale [6], and then growth rates backwards.

Table A 2: Estimated VECM, with an alternative measure of u_t and Impulse Response Functions of the restricted model (Cholesky decomposition, shocks of 1 standard deviation).

	Model 1 (unrestricted)	Model 2 (with restrictions)
w_{t-1}	1.000	1.000
e_{t-1}	0.163 (0.220)	0.000
u_{t-1}	-0.710 (0.117)	-0.850 (0.123)
$logGDP_{t-1}$	2.223 (1.654)	0.000
t	-0.089 (0.115)	0.000
$constant$	-70.587	-35.501
LR test for binding restrictions (rank = 1):		$(\beta_1 = 1, \beta_2 = 0, \beta_4 = 0, \beta_5 = 0)$
Chi-square(3)		3.801
Probability		0.284

Notes: Standard errors in parentheses.
The coefficient β_1 is normalized to one.

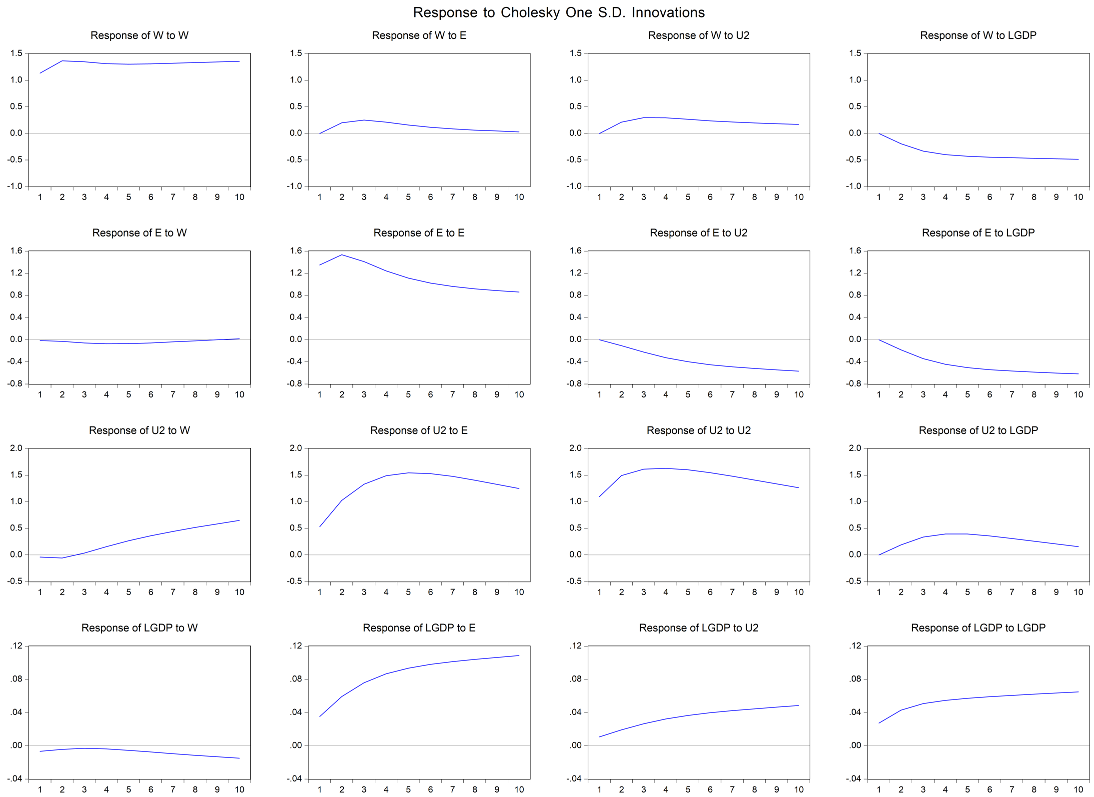


Table A 3: Estimated VECM, with an alternative measure of e_t and Impulse Response Functions of the restricted model (Cholesky decomposition, shocks of 1 standard deviation).

	Model 1 (unrestricted)	Model 2 (with restrictions)
w_{t-1}	1.000	1.000
e_{t-1}	-0.104	0.000
	(0.173)	
u_{t-1}	-0.597	-0.825
	(0.094)	(0.105)
$logGDP_{t-1}$	3.217	0.971
	(1.386)	(0.395)
t	-0.158	0.000
	(0.098)	
$constant$	-56.14972	-45.10190
LR test for binding restrictions (rank = 1): ($\beta_1 = 1, \beta_2 = 0, \beta_5 = 0$)		
Chi-square(3)		0.967
Probability		0.617

Notes: Standard errors in parentheses.
The coefficient β_1 is normalized to one.

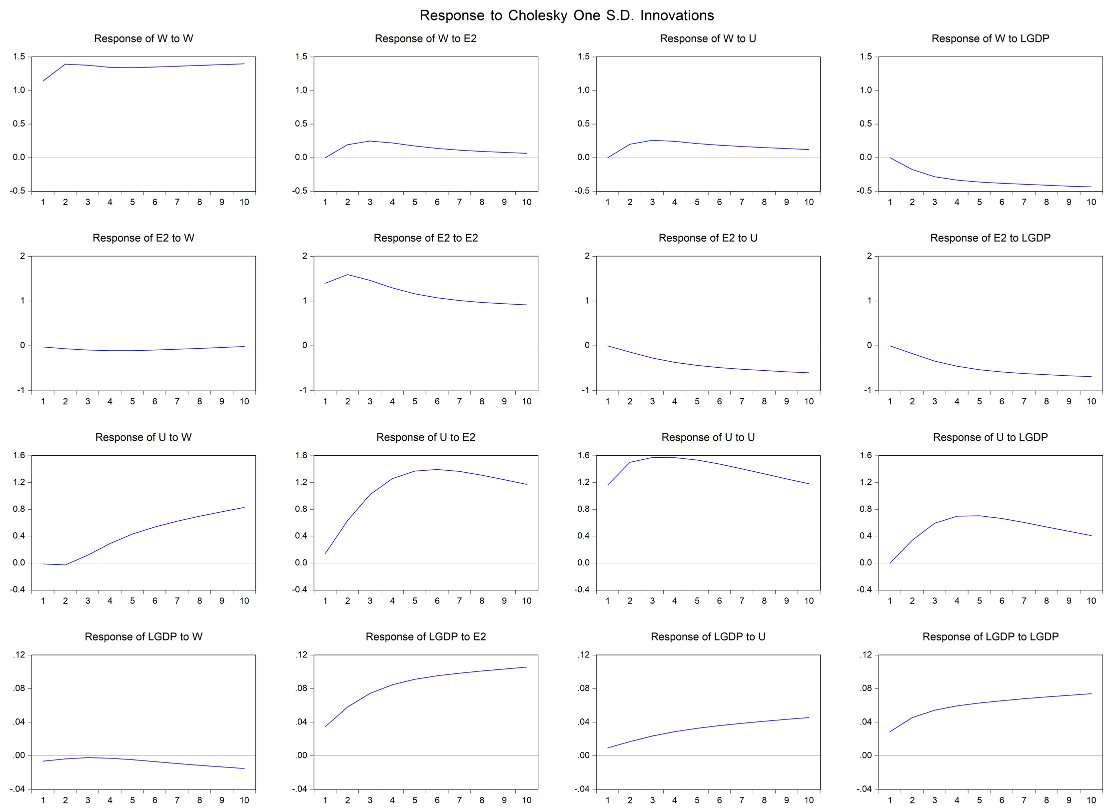


Table A 4: Estimated VECM, using the percentage change of total nominal non-dwellings capital stock, i, instead of $logGDP$ and Impulse Response Functions of the restricted model (Cholesky decomposition, shocks of 1 standard deviation).

	Model 1
w_{t-1}	1.000
e_{t-1}	-0.769 (0.257)
u_{t-1}	-0.796 (0.114)
i_{t-1}	2.059 (0.216)
$constant$	16.209

Notes: Standard errors in parentheses.
The coefficient β_1 is normalized to one.

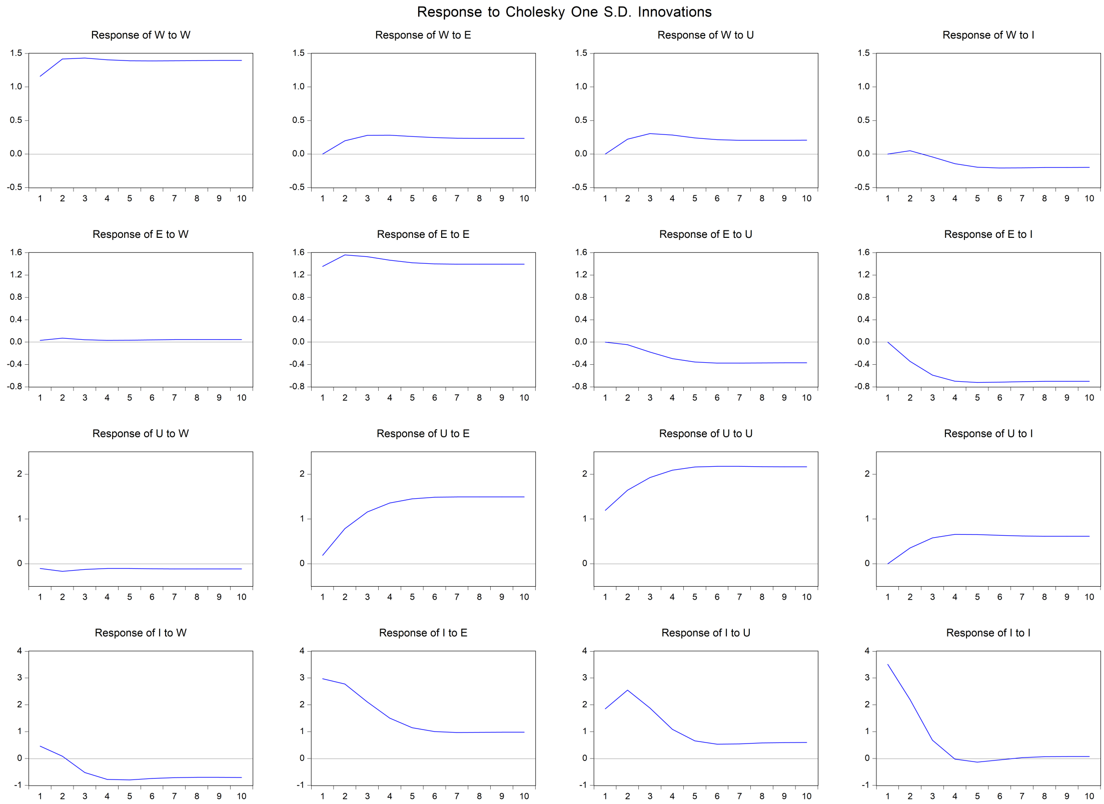


Table A 5: Estimated VECM, using the log of total nominal non-dwellings capital stock, $logK$, instead of $logGDP$ and Impulse Response Functions of the restricted model (Cholesky decomposition, shocks of 1 standard deviation).

	Model 1 (unrestricted)	Model 2 (with restrictions)
w_{t-1}	1.000	1.000
e_{t-1}	-0.234	0.000
	(0.158)	
u_{t-1}	-0.457	-0.509
	(0.074)	(0.084)
$logK_{t-1}$	4.126	4.455
	(1.051)	(1.081)
t	-0.237	-0.251
	(0.072)	(0.077)
$constant$	-55.781	-76.618
LR test for binding restrictions (rank = 1):		$(\beta_1 = 1, \beta_2 = 0)$
Chi-square(3)		1.680
Probability		0.195

Notes: Standard errors in parentheses.
The coefficient β_1 is normalized to one.

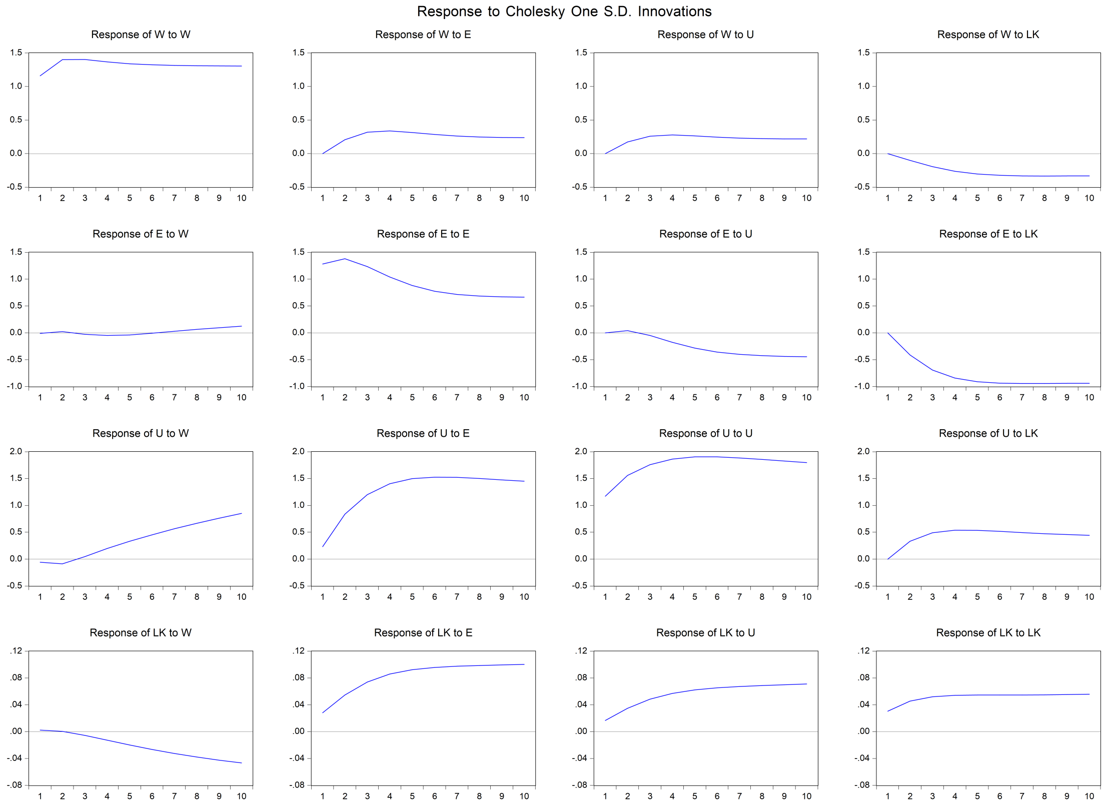


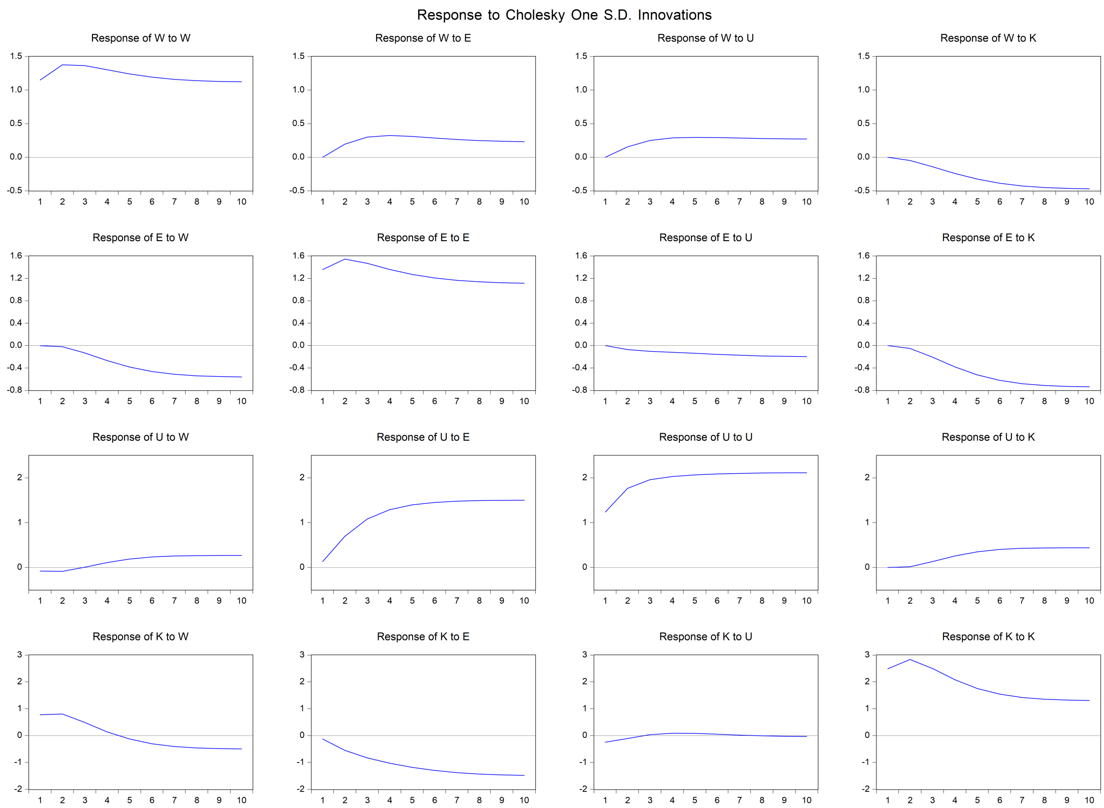
Table A 6: Estimated VECM, using property income from overseas, k, instead of $logGDP$ and Impulse Response Functions of the restricted model (Cholesky decomposition, shocks of 1 standard deviation).

	Model 1 (unrestricted)	Model 2 (with restrictions)
w_{t-1}	1.000	1.000
e_{t-1}	1.090	1.127
	(0.328)	(0.349)
u_{t-1}	-0.146	0.000
	(0.098)	
k_{t-1}	0.914	0.992
	-0.153	(0.166)
constant	-168.1687	-177.4133

LR test for binding restrictions (rank = 1): $(\beta_1 = 1, \beta_2 = 0, \beta_4 = 0, \beta_5 = 0)$

Chi-square(3)	1.482
Probability	0.224

Notes: Standard errors in parentheses. The coefficient β_1 is normalized to one.



Total domestic profits are calculated as follows.

(ii) For 1948-2018, the gross operating surplus (GOS) of all corporations is calculated as GOS of the UK (ONS ABNF) less GOS of general government (ONS NMXV) less GOS of households and nonprofit institutions serving households (ONS QWLS).

(iii) For 1892-1948, the GOS of all corporations is calculated as the sum of the GOS for private companies, the gross trading surplus of public corporations and the gross trading surplus of other public enterprises (Thomas and Dimsdale [6] Worksheet A17, Columns AD, AE and AF respectively).

(iv) A complete series is then obtained by splicing (ii) on to (i).

(v) Total mixed income: for 1948-2018 is from ONS QWLT; for 1892-1948 self-employment income is from Thomas and Dimsdale [6] Worksheet A17 column N, which is then spliced on to the ONS series using the common 1948 figure.

(vi) The profit component of mixed income is determined by applying the ratio of the sum of (ii) and (iv) to GDP at factor cost.

(vi) Then the openness variable, k, is the ratio of (i) to the sum of (i) and (iv) and (vi).

6 Disentangling the wage share

Unfortunately, only very limited data exist for the UK economy that precisely distinguish different categories of employees. Census of Production data provide a continuous series for the Production Industries (Mining, Manufacturing and Utilities) for the years 1974-1995. Data are reported on wages paid to manual workers (operatives) and gross value added, and hence a manual worker wage share in production industries can be constructed. But there is no analogous sectoral employment rate, and so we have to assume that the economy-wide employment rate used in the paper can be used as a proxy for that of Production industries. This is difficult because of the secular decline of employment in Production industries. With that caveat, if WSER cycles can be found for the economy as a whole, then one would expect them to exist in Production industries.

We apply the same methodology as in section 4 of the paper to the raw data. First, Figure A8 displays three cycles in deviations from trend of the wage share in gross value added of manual workers (operatives) in production industries (horizontal axis) plotted against the deviations from trend of the national employment rate (vertical axis). As in the paper, the 1976-81 and 1986-93 cycles are clockwise, but unlike in the paper the 1981-86 data appear to show an anti-clockwise rather than an indeterminate pattern.

However, the long-run behaviour of the income share of the manual working class confirms, indeed further strengthens the doubts on the empirical validity of SDT discussed in the paper. For the equilibrium values, the centres of the WSER cycles, around which the wage share and the rate of employment fluctuate, vary significantly over time, and there is a pronounced long-run decline in the operatives' wage share in production industries, as illustrated in Figure A9.

Concerning the data sources for Figures A8 and A9:

The wage share is Wages and Salaries of Operatives in Production Industries (mining and quarrying; manufacturing; and electricity, gas and water supply) divided by Gross Value Added in Production Industries, both from Business Monitor (Census of Production), PA1002, Table 2, Annual Years [1]. (Employers' National Insurance Contributions are not included in Wages and Salaries of Operatives.)

The employment rate and trend is the same as in the main paper.

Trends and deviations from trend are derived in the same way as in the main paper (from a Hodrick-Prescott filter using the default Eviews specification for annual data).

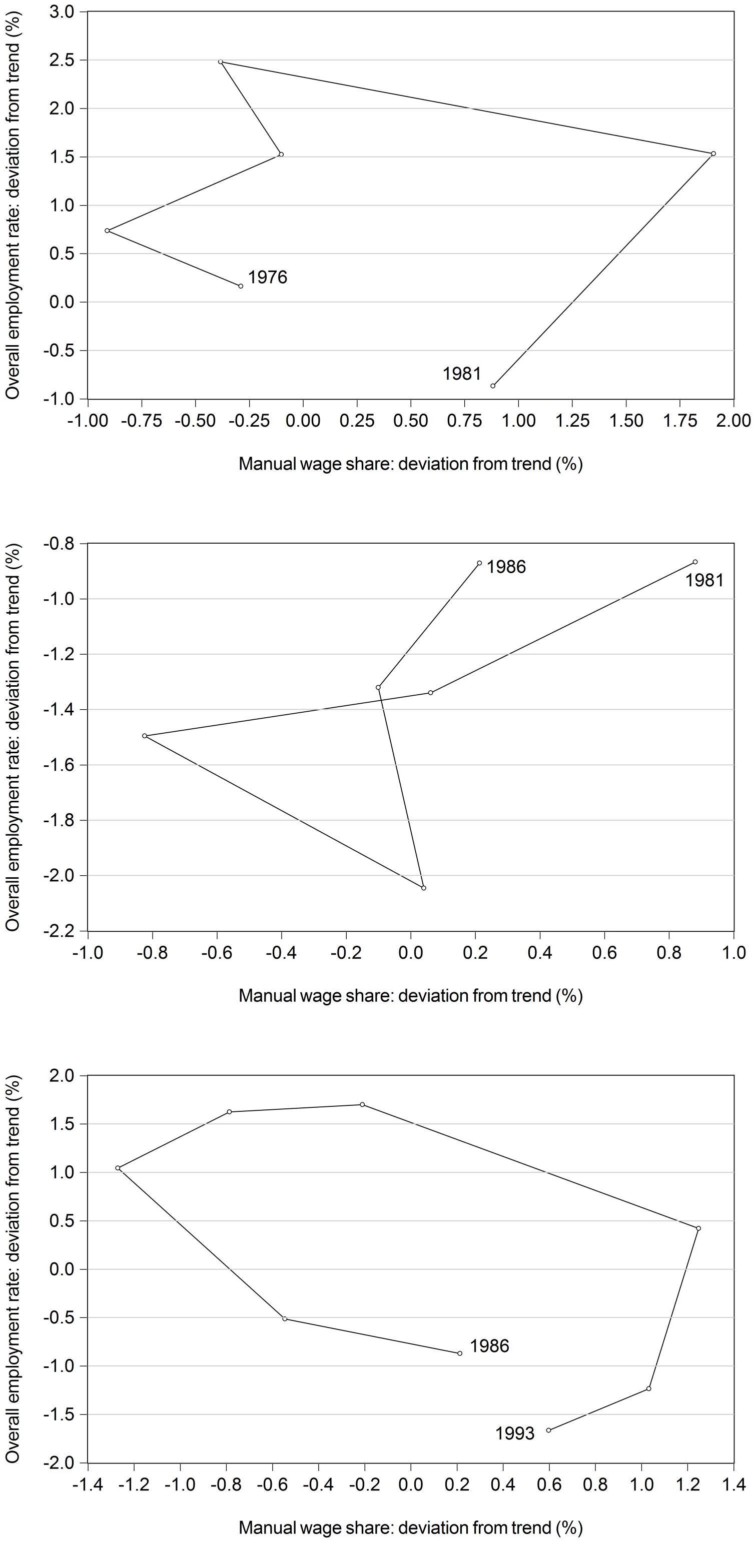


Figure A 8: *Three WSER Cycles, UK Operatives, 1976-1993.*

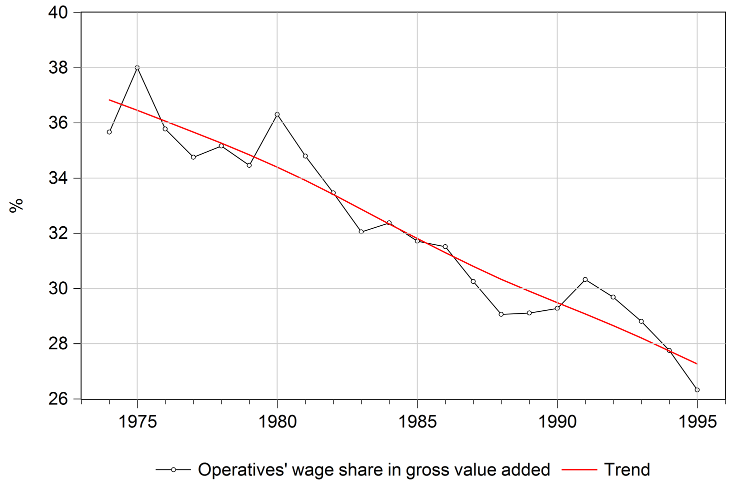


Figure A 9: *Production Industries: Operatives' Wage Share (Raw Data and Trend), UK, 1974-1995*

References

[1] Central Statistical Office (1995), *Business Monitor : PA1002: Annual Census of Production: Summary Volume* Annual Years, London: HMSO

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