Wage Led Aggregate Demand in the United Kingdom

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Abstract

The wage led aggregate demand hypothesis is examined for the United Kingdom over the period 1971 - 2007. Existing studies disagree on the aggregate demand regime for the UK, and this appears to be due to differing empirical approaches. Studies relying on equation-by-equation estimation procedures tend to find support for wage led aggregate demand in the UK, while the single study using systems estimation finds no support for the hypothesis. In order to resolve this incongruity, we test the wage led aggregate demand hypothesis in the UK using VAR models estimated on quarterly data. We use a liberal partial identification strategy based on movements in real earnings rather than in the labour share. The results provide support for the wage led aggregate demand hypothesis during the period of study.

Keywords: Real Earnings, Income Distribution, Business Cycles.

JEL Codes: E32, E25, B50, E12.

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1 Introduction

The wage led aggregate demand hypothesis can be traced to the work of Michał Kalecki and Josef Steindl via Rowthorn (1981), Dutt (1984), and Bhaduri and Marglin (1990). The theoretical framework supposes that total consumption is an increasing function of the labour share, and total investment and net exports are non-increasing functions of the labour share. Depending on the relative strength of these distributive effects, an increase in the labour share will either increase or decrease aggregate demand, and thereby gross domestic product (GDP). The wage led aggregate demand hypothesis states that the distributive effect on demand works in favour of wages: an increase in the labour share will lead to an increase in GDP.

The interplay between the distribution of income and the level of aggregate demand has been argued, by a number of prominent economists, to be of central importance in rethinking macroeconomic theory in light of the 2008 crisis (e.g. Stiglitz 2011). The wage led aggregate demand hypothesis itself has been influential in those policy-focused international institutions broadly aligned with developing countries and the labour movement (UNCTAD 2010, Lavoie and Stockhammer 2012). However, a variety of estimation procedures and data types have been used to test the hypothesis, and different studies often come to different conclusions. This is particularly the case in the UK. Studies relying on equation-by-equation estimation procedures, for example, tend to find support for wage led aggregate demand in the UK. This is the case in Bowles and Boyer (1995), Naastepad and Storm (2007), Hein and Vogel (2008), Onaran and Galanis (2014), and Obst and Onaran (2015). The single study using a systems estimation procedure, Stockhammer and Onaran (2004), finds no support for the hypothesis.

The purpose of the present paper is to attempt to resolve this incongruity by testing the wage led aggregate demand hypothesis for the UK using VAR models. Given this, our approach is based on identified shocks to real earnings, rather than the labour share or total labour income. Modelling the labour share directly almost forces the researcher to use identification restrictions based on the Bhaduri-Marglin model, or some adaptation of it, which is the approach taken in the bulk of the existing literature. Focusing on real earnings allows us to take a liberal approach to identification, so we do not have to specify a particular structural model with a large number of degrees of freedom. Essentially, instead of identifying shocks to the labour share directly, we estimate movements in the labour share indirectly, by estimating the responses of GDP and total employment to identified shocks to real earnings.

Our focus in this paper is solely on short run changes in the functional income distribution, and we do not estimate long run relationships. This is, perhaps, the simplest approach to the wage led aggregate demand hypothesis, although it runs counter to arguments made in Blecker (2014). While we are not averse to the proposition that income distribution effects operate at low frequencies, it seems likely that the best way to approach this problem empirically would be via cross-country growth regressions, or using long time series at annual frequencies. The foregoing, in addition, explains why we refer to the wage led aggregate demand hypothesis throughout the paper, rather than the wage led growth hypothesis as in Bhaduri (2008).

The rest of the paper is organised as follows. Section 2 discusses the wage led aggregate demand hypothesis in the context of movements in real earnings, rather than the labour share, and compares this to the existing literature. With this background, section 3 discusses our empirical approach and identification strategy. Section 4 discusses our data sources and variable definitions, and section 5 presents the estimation results. Section 6 concludes, and discusses the implications of our results for theory and policy.

2 The Wage Led Aggregate Demand Hypothesis

Consider a general model of the business cycle, where the endogenous variables are consumption (C), investment (I), net exports (X), and GDP (Y). Assume that GDP is determined by the aggregate demand identity, and the components of aggregate demand are functions of GDP and the labour share (h), such that,

$$Y = C + I + X, \tag{1}$$

$$C = C(Y, h), \tag{2}$$

$$I = I(Y, h), \tag{3}$$

$$X = X(Y, h), \tag{4}$$

suppressing exogenous government spending. The total differentials are given by,

$$dY = dC + dI + dX, \tag{5}$$

$$dC = \frac{\partial C}{\partial Y} dY + \frac{\partial C}{\partial h} dh, \tag{6}$$

$$dI = \frac{\partial I}{\partial Y} dY + \frac{\partial I}{\partial h} dh, \tag{7}$$

$$dX = \frac{\partial X}{\partial Y} dY + \frac{\partial X}{\partial h} dh, \tag{8}$$

and by substituting (6) - (8) into (5) and rearranging, we have the total derivative,

$$\frac{dY}{dh} = \left(\frac{\partial C}{\partial h} + \frac{\partial I}{\partial h} + \frac{\partial X}{\partial h} \right) \left(1 - \frac{\partial C}{\partial Y} - \frac{\partial I}{\partial Y} - \frac{\partial X}{\partial Y} \right)^{-1}. \tag{9}$$

Equation (9) summarises the wage led aggregate demand hypothesis. One usually assumes that the second term in brackets is positive, that consumption is increasing in the labour share, and that both investment and net exports are non-increasing in the labour share. If the positive effect of an increase in the labour share on consumption outweighs any negative effects on investment and net exports, then the total effect on GDP will be positive.

There is a rather large literature testing the wage led aggregate demand hypothesis, the bulk of which estimates equations of the form (2) - (4) on an equation-by-equation basis.

The studies that apply this method to UK data are Bowles and Boyer (1995), Naastepad and Storm (2007), Hein and Vogel (2008), Stockhammer and Stehrer (2011), Onaran and Galanis (2014), and Obst and Onaran (2015). All of these papers, apart from Stockhammer and Stehrer (2011), find that aggregate demand in the UK is wage led. There is an issue, however, in assuming that the labour share is exogenous. While this is a legitimate procedure in a thought experiment of the sort described above, it is potentially problematic when testing the theory. Particularly, issues of endogeneity bias may cast doubt on the results.

While the issue of endogeneity bias is often discussed in the empirical literature, it is not often dealt with. The natural solution would be to estimate a VAR in the components of aggregate demand and the labour share, but this runs into a severe sample size problem given the number of parameters to be estimated. One solution is to estimate a VAR in GDP and the labour share, assuming a reduced form specification, following the study of Barbosa-Filho and Taylor (2006) for the USA. In this case one can derive impulse response functions which roughly correspond to (9). Unfortunately, at this point, one faces an identification problem. Specifically, meaningful impulse response functions require orthogonal shock processes, and the notion of orthogonal GDP and labour share shocks is just as problematic as treating the labour share itself as exogenous.

One notable solution to this conundrum is that of Stockhammer and Onaran (2004), which estimates a structural VAR model based explicitly on Bhaduri and Marglin (1990). This circumvents the problem of imagining orthogonal GDP and labour share shocks by an appeal to a structural model with a large number of degrees of freedom. The authors find that shocks to the functional distribution of income have essentially no effect on capacity utilisation, and thus find no support for the wage led aggregate demand hypothesis. This is an incongruous result made particularly worrying by the aforementioned estimation bias in the group of studies that find that the UK is wage led.

The present paper aims to resolve this incongruity. As with Stockhammer and Onaran (2004), we estimate VAR models for the UK. Unlike the latter, we take an indirect approach by disaggregating the labour share into real earnings, total employment, and GDP. We are then left with a model in GDP (Y), total employment (L), and real earnings (w),

$$Y = Y(w, L), \tag{10}$$

$$L = L(w, Y), \tag{11}$$

$$w = w(Y, L). \tag{12}$$

Here, (10) is an aggregate demand curve, (11) is an employment curve, and (12) is an earnings curve. While we expect the earnings curve to be increasing in both GDP and employment, both $\partial Y/\partial w$ and $\partial L/\partial w$ are ambiguous. If the former is positive, then a positive shock to the earnings curve increases aggregate demand. This case is illustrated in the left panel of figure 1, which plots an upward sloping earnings curve and upward sloping aggregate demand curve in (w, Y) space.

Given the above, we take advantage of the fact that exogenous changes in the labour share in the heterodox perspective are usually held to be driven by changes in workers' bargaining power. This view is summarised in the following passage discussing policies associated with the wage led aggregate demand hypothesis:

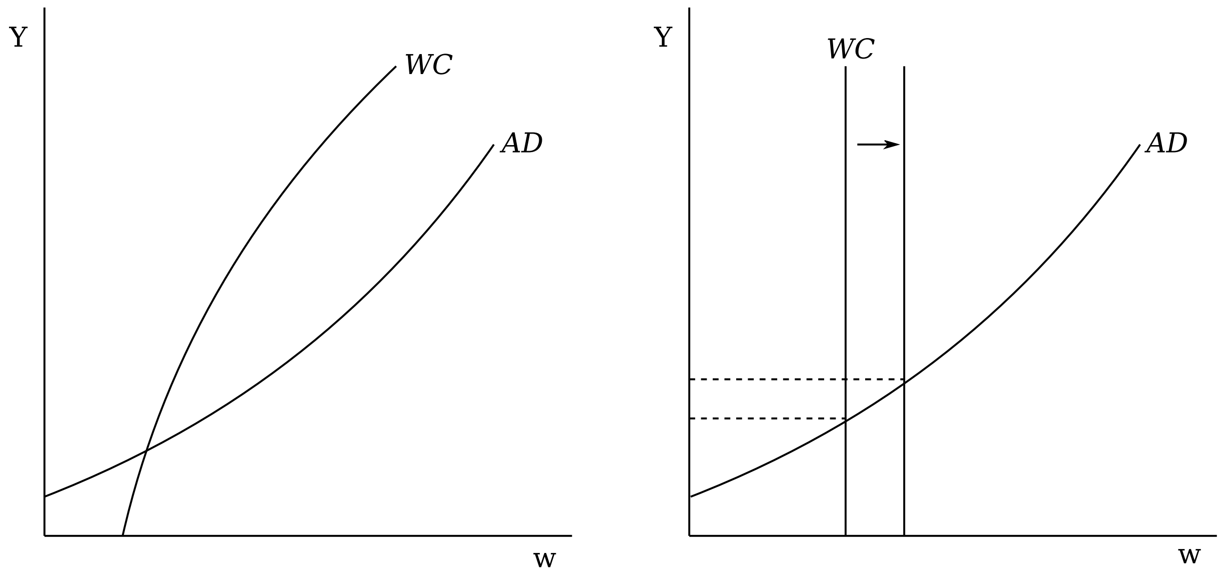

Figure 1: Illustrating the wage led aggregate demand hypothesis.

> "Pro-labour policies . . . are often referred to as policies that strengthen the welfare state, labour market institutions, labour unions, and the ability to engage in collective bargaining (e.g., by extending the reach of bargaining agreements to non-unionised firms). Pro-labour policies are also associated with increased unemployment benefits, higher minimum wages and a higher minimum wage relative to the median wage, as well as reductions in wage and salary dispersion" (Lavoie and Stockhammer 2012).

In light of this, we will interpret identified real earnings shocks as bargaining power shocks. We will then consider the data to be consistent with the wage led aggregate demand hypothesis if positive real earnings shocks lead to increases in both GDP and the labour share. This case is illustrated in the right panel of figure 1, under the assumption that the change in total employment is non-negative and $\partial w/\partial Y = 0$. Thus we take an indirect approach to testing the wage led aggregate demand hypothesis, avoiding issues of endogeneity bias and the need to construct orthogonal GDP and labour share shocks.

This approach is dissimilar to the existing literature testing the wage led aggregate demand hypothesis, and may be compared to the econometric literature studying the relationship of real wages, output, and employment over the business cycle. This literature goes back to Rueff, Dunlop, and Tarshis, and Brandolini (1995) provides a comprehensive survey of the literature up to the early 1990s. A notable recent study is McFarlane et al (2014), which studies the business cycle co-movements of Canadian wages, output, and employment, using the VAR methodology. In addition, we may usefully compare our approach to the New Keynesian theories of real wages and aggregate demand, where exogenous movements in the real wage can be driven by productivity shocks as well as bargaining power shocks. An example is Balmaseda et al (2000), which finds that positive real wage shocks increase aggregate demand, but these shocks are interpreted as productivity shocks rather than bargaining power shocks.

While our approach is formally similar to the econometric literature surveyed in Brandolini (1995) and the New Keynesian literature, it must be stressed that our goal is very different. Unlike these literatures, we are not primarily concerned with the relationship between output and the real wage (or real earnings). Instead, we are primarily concerned with the relationship between output and the labour share, and will only consider the data to be consistent with the wage led aggregate demand hypothesis if positive real earnings shocks lead to increases in both GDP and the labour share. This is not often a concern of the aforementioned literatures, for which the functional distribution of income is not considered important on the demand side, although there is an issue of observational equivalence to bear in mind[1]. This is discussed with the data in section 4, after our identification strategy is discussed in section 3.

3 Empirical Approach

As discussed in section 2, we model movements in real earnings rather than the labour share, and follow Stockhammer and Onaran (2004) by estimating the following,

$$Az_t = \alpha + \sum_{i=1}^{p} A_i z_{t-i} + u_t, \tag{13}$$

$$z_t = \mu + \sum_{i=1}^{p} C_i z_{t-i} + \epsilon_t, \tag{14}$$

where (13) is the structural model, and (14) is the reduced form. The vector z_t contains GDP, total employment, and real earnings, u_t is a white noise vector process with $u_t \sim N(0, I)$, and ϵ_t is a white noise vector process with $\epsilon_t \sim N(0, \Sigma)$. This leads to an identification problem: recovering A from the estimated reduced form (14). Our identification strategy follows the short run restriction approach described in Sims (1986) by specifying zero elasticities within the period. From (13) and (14) we have $\epsilon_t = A^{-1}u_t$, or $A\epsilon_t = u_t$. Expanding, we have:

$$\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} \epsilon_Y \\ \epsilon_L \\ \epsilon_w \end{pmatrix} = \begin{pmatrix} u_Y \\ u_L \\ u_w \end{pmatrix}. \tag{15}$$

As we are primarily concerned with the effects of real earnings shocks, we do not fully identify the model. Instead, we rely on two restrictions to A to achieve partial identification. Specifically, we assume $a_{31} = a_{32} = 0$. It is well established that nominal wage and price contracts are updated infrequently and set in advance of production (see e.g. Druant et al (2012) and the references therein). In addition, the relevant output and employment data are released with a lag, and are subject to substantial uncertainty concerning future revision. Finally, wage setting is known to depend on a number of largely non-economic considerations, including notions of fairness that evolve very slowly (Bewley 1999). Given

[1]Positive wage shocks in New Keynesian models usually reduce output on impact. Interestingly, however, a weak wage led aggregate demand mechanism is incorporated into the Bank of England's COMPASS model, where a wage mark-up shock "temporarily increases labour income and consumption of [liquidity] constrained households, which is sufficient to increase total consumption in the near term. This effect means that GDP does not fall immediately" (Burgess et al 2013a, 2013b: B17). Also see Charpe and Kühn (2015).

this, and postponing a discussion of the components of earnings until section 4, it seems reasonable to assume that real earnings do not react to aggregate demand or labour demand movements within the period, which supplies us with the two identification restrictions, $a_{31} = a_{32} = 0$. Thus (15) reduces to,

$$\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{pmatrix} \begin{pmatrix} \epsilon_Y \\ \epsilon_L \\ \epsilon_w \end{pmatrix} = \begin{pmatrix} u_Y \\ u_L \\ u_w \end{pmatrix}. \tag{16}$$

The restrictions embodied in (16) imply that real earnings are the "most exogenous" variable in our system, which is broadly in line with the Post Keynesian approach to wage led aggregate demand discussed above. Given this, (16) is not fully identified, but the real earnings shock u_w is identified, and the impulse response functions and variance decompositions for u_w can be computed without further identification restrictions. In particular, the impulse response functions and variance decompositions for u_w in (16) are equivalent to any Cholesky decomposition in which real earnings are ordered first (as A is block recursive; see e.g. Christiano et al (1999) or Garratt et al (2012)).

4 Data

4.1 Sources

As explained in sections 2 and 3, we estimate VARs in GDP, total employment, and real earnings. The raw data are as follows: non-seasonally adjusted (NSA) quarterly nominal GDP from the UK quarterly national accounts (code BKTL), seasonally adjusted (SA) nominal GDP from the quarterly national accounts (code YBHA), NSA UK real (chain value) GDP from the quarterly national accounts (code BKVT), SA UK real (chain value) GDP from the quarterly national accounts (code ABMI), SA total employment from the Labour Force Survey, NSA average weekly earnings from the ONS Employment and Earnings publications (codes MD9M and KA46), and the NSA retail price index from the ONS MM23 Consumer Price Indices publication (code CDKO). Only the GDP series are available both SA and NSA; the historical earnings and price data are only available NSA, and the employment data are only available SA (as the quarterly data are interpolated on an SA basis prior to 1992).

Given the above, we construct two NSA real earnings series using average earnings deflated by the retail price index and average earnings deflated by the NSA GDP deflator, where the latter is given by the ratio of NSA nominal and NSA real GDP. We then seasonally adjust these NSA real earnings series using the automated Census X-13 procedure in EViews, which yields two SA real earnings series. We can then estimate four VARs in total: two VARs using NSA real GDP, NSA real earnings, and SA total employment (where the first uses RPI deflated earnings, and the second uses GDP deflated earnings), and two VARs using SA real GDP, SA real earnings, and SA total employment (where the first uses RPI deflated earnings, and the second uses GDP deflated earnings). Thus we use SA and NSA data, and two different earnings deflators, to increase the robustness of our results. All of the

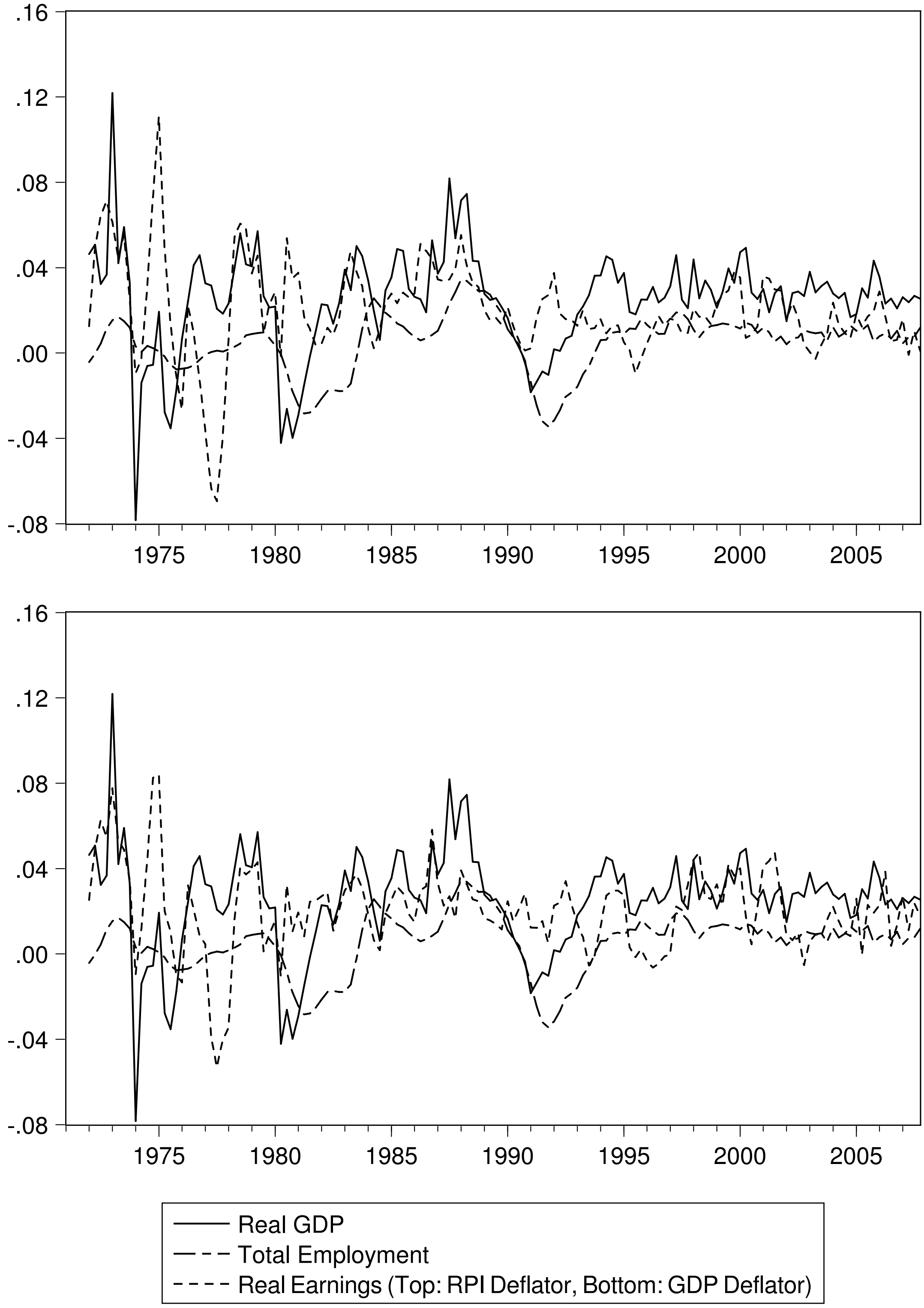

Figure 2: NSA Real GDP, SA total employment, and NSA real earnings series, four quarter log differences, 1972 - 2007.

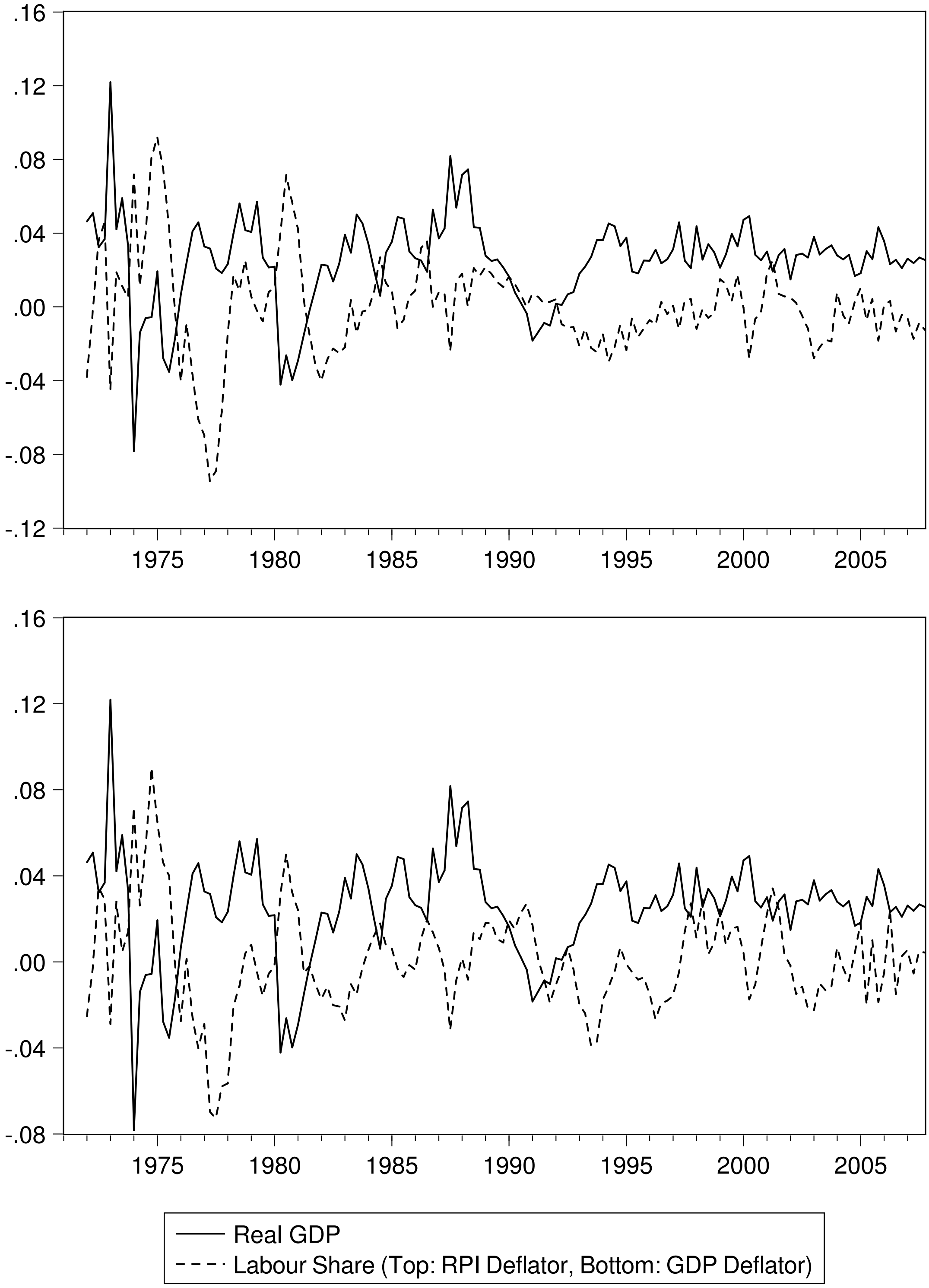

Figure 3: NSA GDP and NSA labour share approximation, four quarter log differences, 1972 - 2007.

series run from 1971 to 2014, although on inspection there appears to be a large structural break in the real earnings series around 2008, which causes fairly serious problems for our estimates. Given this, we limit our sample size to end at 2007Q4.

4.2 Unit Roots Tests

With respect to the SA data, three different unit root tests were employed to determine the order of integration of the series: the Augmented Dickey-Fuller test (ADF; Said and Dickey 1984); the Dickey–Fuller Generalized Least Squares test (DF-GLS; Elliot et al. 1996); and the Modified Phillips-Perron test (M-PP; Ng and Perron 2001). We employed OLS-detrended data as the autoregressive spectral estimation method in the M-PP test since, according to Perron and Qu (2007), this method can be considered as a solution to the drawback that (for non-local alternatives) the power of the M-PP tests can be very small. The highest lag order (l_{max}) selected to carry out the three tests was determined from the sample size according to the method proposed by Schwert (1989): $l_{max} = \left[12\,(144/100)^{0.25}\right] \approx 13$. We employed different methods to determine the optimal lag order in each test: the Schwarz information criterion was employed for the ADF test, the general-to-specific procedure (Ng and Perron 1995) was employed for the DF-GLS test, and the Modified Akaike Information Criterion (Ng and Perron 2001) was employed for the M-PP test.

Table A1 in the appendix reports the different linear unit root tests that best capture the actual behaviour of the series in order to avoid misspecification. All tests were carried out including a constant and a trend as exogenous regressors for the different series. The tests shows that it is not possible to reject the null hypothesis of a unit root at the 5% level of significance in the majority of the log-levels of the series, and that the null hypothesis is rejected when the first differences of the log-levels of the series are considered. Hence, it is possible to conclude that the growth rates of the series can be characterised as $I(0)$ processes.

With respect to the NSA data, we employed the HEGY test for seasonal unit roots (Hylleberg et al 1990), using the HEGY test add-in for EViews. This tests for unit roots at seasonal frequencies, indicating how the data should be differenced (in order to prevent over-differencing and the incorporation of artificial moving average components). The test results are presented in Table A2 in the appendix. All tests were carried out including a constant, a trend, and seasonal dummies as exogenous regressors for the different series. The different tests show that none of the log-levels of the series can be considered as stationary series since the null hypotheses that $\pi_1 = 0$, $\pi_2 = 0$ and $\pi_3 = \pi_4 = 0$ are not rejected (see Hylleberg et al 1990)[2]. Likewise, it is possible to observe that the four-quarter differences of the log-levels of series can be considered as stationary series since the null hypotheses that $\pi_1 = 0$, $\pi_2 = 0$ and $\pi_3 = \pi_4 = 0$ are not rejected.

As discussed above, we estimate four VARs in total: two VARs using NSA real GDP, NSA real earnings, and SA total employment (where the first uses RPI deflated earnings, and the second uses GDP deflated earnings), and two VARs using SA real GDP, SA real earnings, and SA total employment (where the first uses RPI deflated earnings, and the second uses GDP deflated earnings). Given the results of the unit roots tests, all variables

[2]There appears to be no non-seasonal unit root in the log-level of the GDP deflated earnings since the null hypothesis that $\pi_1 = 0$ is rejected in this case. The slight ambiguities in the unit root tests should not create too much doubt in the inference, however, as all series are expected to be intrinsically non-stationary.

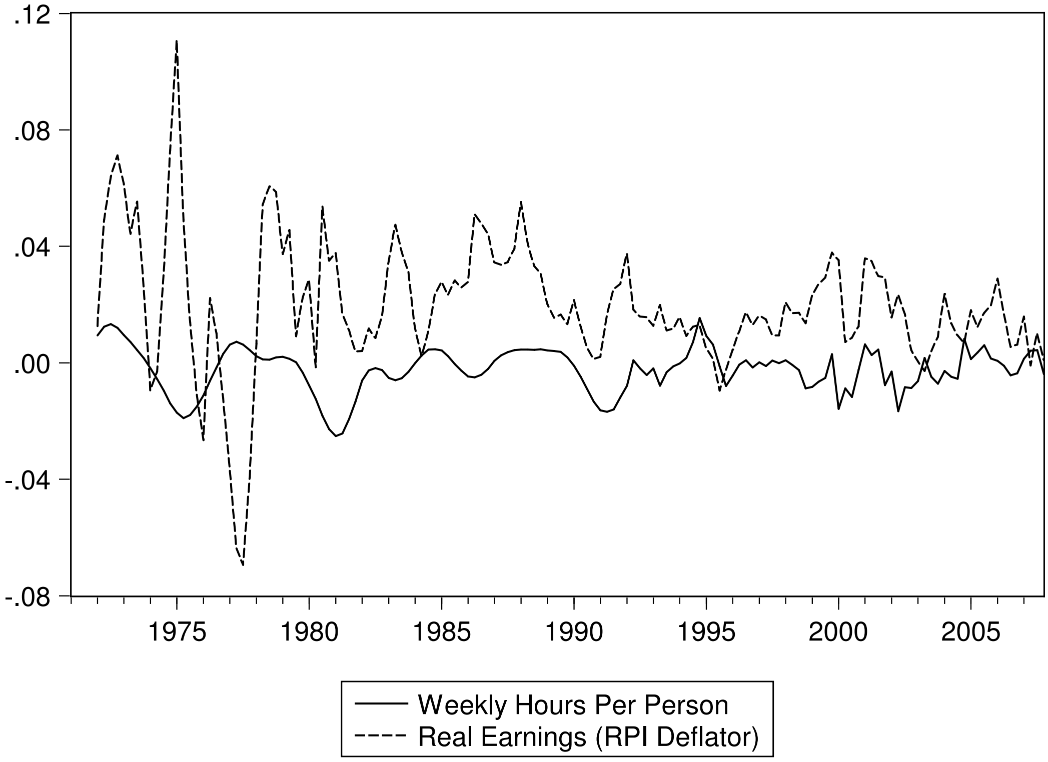

Figure 4: NSA real earnings and SA hours per person, four quarter log differences, 1972 - 2007.

in the first two VARs are in four quarter log differences, and all variables in the second two VARs are in one quarter log differences.

4.3 Description

Figure 2 plots the four quarter log differences of NSA real GDP, NSA real earnings, and SA total employment, from 1972 - 2007. While real earnings appear to be mildly pro-cyclical and less volatile than GDP, total employment follows GDP with a considerable lag and is much less volatile than GDP, even allowing for the interpolated data prior to 1992. The real earnings series appear to differ slightly depending on the deflator used, with the differences being most pronounced in the late 1970s and late 1990s. Figure 3 plots four quarter log differences of NSA real GDP and the NSA labour share, where the latter is approximated by the four quarter log difference of NSA real earnings plus the four quarter log difference of SA total employment minus the four quarter log difference of NSA real GDP. This figure illustrates the well known counter-cyclicality of the labour share, in contrast with the mild pro-cyclicality of real earnings illustrated in figure 2.

Two final points must be noted. First, the wage led aggregate demand hypothesis, as we interpret it, requires a positive real earnings shock to increase both GDP and the labour share, which might appear inconsistent with the counter-cyclicality of the labour share at first glance. However, all this implies is that shocks to real earnings that increase both the labour share and GDP cannot be a significant source of fluctuations in either variable, and the wage led aggregate demand hypothesis is thus perfectly consistent with a counter-cyclical labour share. This conjecture, in fact, is supported by the variance decomposition analyses presented in section 5. Second, average earnings are given by the average hourly wage multiplied by average hours worked per person, and thus it is possible that the mild pro-cyclicality of real earnings is driven in the main by pro-cyclical hours worked. Moreover, a positive shock to real earnings could be interpreted as a positive shock to hours worked per person, which does not support an interpretation of earnings shocks as bargaining power shocks. However, we have good reason to believe that the bulk of fluctuations in average weekly earnings are accounted for by fluctuations in the hourly wage. Figure 4 plots the four quarter log difference of NSA average weekly earnings deflated by the RPI deflator and the four quarter log difference of an estimate of SA weekly hours worked per person (total weekly hours, LFS code YBUS, divided by total employment as above). The hours series is considerably less volatile than the real earnings series over the majority of the sample, and the contemporaneous correlation coefficient between the two series is negative and not significantly different from zero at the 5% level. Thus we expect the bulk of fluctuations in real earnings to be due to real wage fluctuations, and we do not expect positive shocks to real earnings to be the result of increases in hours worked[3].

5 Results

5.1 Reduced Form Estimates

As discussed in sections 2, 3 and 4, we estimate VAR models in GDP, total employment, and real earnings. We estimate four reduced form VARs in total: two VARs using NSA real GDP, NSA real earnings, and SA total employment (where the first uses RPI deflated earnings, and the second uses GDP deflated earnings), and two VARs using SA real GDP, SA real earnings, and SA total employment (where the first uses RPI deflated earnings, and the second uses GDP deflated earnings). All series in the first two VARs are in four quarter log differences, and all series in the second two VARs are in one quarter log differences, following the unit root tests described in section 4.

First, we estimate the two reduced form VARs with NSA real GDP, NSA real earnings, and SA total employment, where the first uses RPI deflated earnings, and the second uses GDP deflated earnings. The AIC lag length criteria for both the RPI deflator model and the GDP deflator model indicate 10 lags, and 10 lags also results in reasonable statistics for residual autocorrelation. Both models with 10 lags are stable, with all roots lying within the unit circle. In addition, we cannot reject the null of homoskedasticity using the White test for either model. Although the simple reduced form models appear to be well specified in terms of residual autocorrelation and heteroskedasticity, residual normality test results are unsatisfactory. Bearing this in mind, we choose 10 lags for both reduced form VARs. Detailed tables of results for the specification tests can be found in table B1 in the appendix.

Second, we estimate the two reduced form VARs with SA real GDP, SA real earnings, and SA total employment, where the first uses RPI deflated earnings, and the second uses

[3]Our results are robust to replacing the weekly earnings series with an estimated hourly earnings series constructed using the ONS hours data, although this reduces our ability to infer labour share movements from the results.

GDP deflated earnings. The AIC lag length criteria for both the RPI deflator model and the GDP deflator model indicate 3 lags, but both models with 3 lags appear to suffer from residual autocorrelation and heteroskedasticity. However, reasonable statistics for residual autocorrelation and heteroskedasticity are achieved in models with 10 lags as before (although the RPI deflator model suffers from heteroskedasticity problems even with 10 lags). Both models with 10 lags are stable, with all roots lying within the unit circle. Finally, both models again suffer from residual normality problems[4]. Bearing this in mind, we choose 10 lags for both reduced form VARs. Detailed tables of results for the specification tests can be found in table B2 in the appendix.

5.2 Impulse Response Functions

As discussed in section 3, we rely on a partial identification strategy that isolates shocks to real earnings without making strong assumptions about the remaining direct and indirect interactions. Figure 5 plots the impulse response functions and 95% confidence bands, for all three variables, in response to a positive shock to the earnings curve based on this partial identification, for the models with NSA real GDP, NSA real earnings, and SA total employment. Precisely, we use a Cholesky decomposition with ordering: real earnings, real GDP, total employment, which as discussed in section 3 is equivalent to the ordering: real earnings, total employment, real GDP. Figure 5 plots the responses for the model with RPI deflated earnings in the left three panels, and responses for the model with GDP deflated earnings in the right three panels. It is immediately apparent that a positive real earnings shock causes an increase in GDP on impact, and has no significant effect on total employment. The differences between the two sets of impulse response functions are minor, with the obvious difference being the larger effect of the real earnings shock on GDP in the model with GDP deflated earnings. Aside from this, both sets of impulse response functions imply that the positive effect on GDP growth of a real earnings shock declines to zero after a year, and that the effect on total employment is negligible.

Figure 6 plots the impulse response functions and 95% confidence bands, for all three variables, in response to a positive shock to the earnings curve based on this partial identification, for the models with SA real GDP, SA real earnings, and SA total employment. Figure 6 plots the responses for the model with RPI deflated earnings in the left three panels, and responses for the model with GDP deflated earnings in the right three panels. As in the models with NSA data, a positive real earnings shock causes an increase in GDP on impact, and has no significant effect on total employment. The differences between the two sets of impulse response functions are minor, and the effects of a real earnings shock on GDP at impact are similar to those in the models with NSA data. The largest difference between the impulse response functions in the models with SA data and the models with NSA data is the length of the effect: a positive real earnings shock appears to have a positive effect on GDP that only lasts a single quarter in the models using SA data[5].

The conclusion that positive shocks to real earnings increase aggregate demand does not, by itself, lead to the conclusion that the wage led aggregate demand hypothesis is supported. As noted in section 2, we also require that the labour share increases in response to an

[4]We added dummy variables in previous specifications to deal with this problem, which was more successful in the models with NSA data than with SA data. The results were not materially affected, however, so the final specifications do not include dummy variables.

[5]All confidence bands are computed using the bootstrap procedure in EViews with 1000 repetitions.

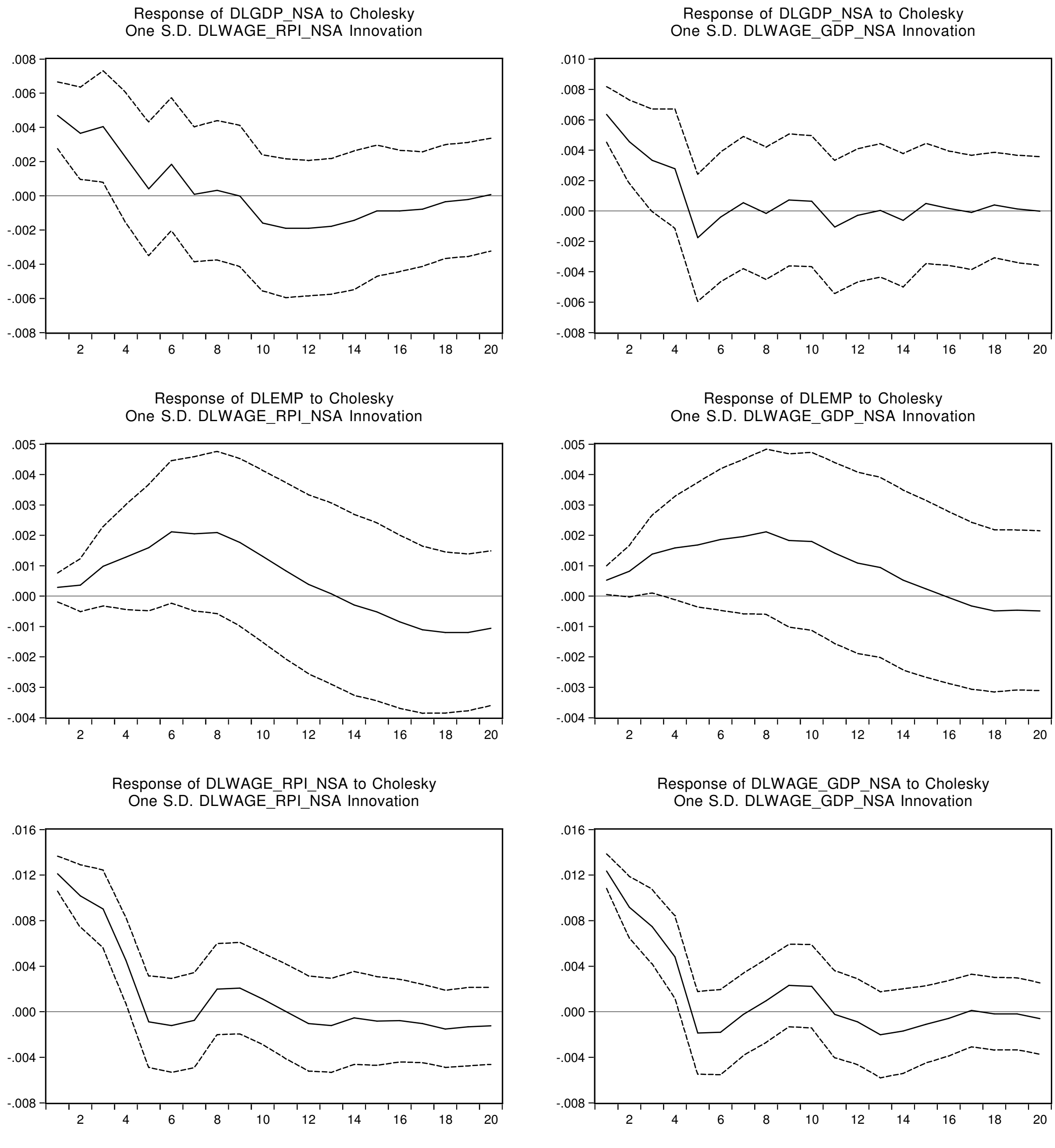

Figure 5: Impulse response functions of GDP (top), employment (middle), earnings (bottom), to a positive real earnings shock, VARs with NSA real GDP, NSA real earnings, and SA total employment (four quarter log differences). Left panel: RPI deflated earnings, right panel: GDP deflated earnings.

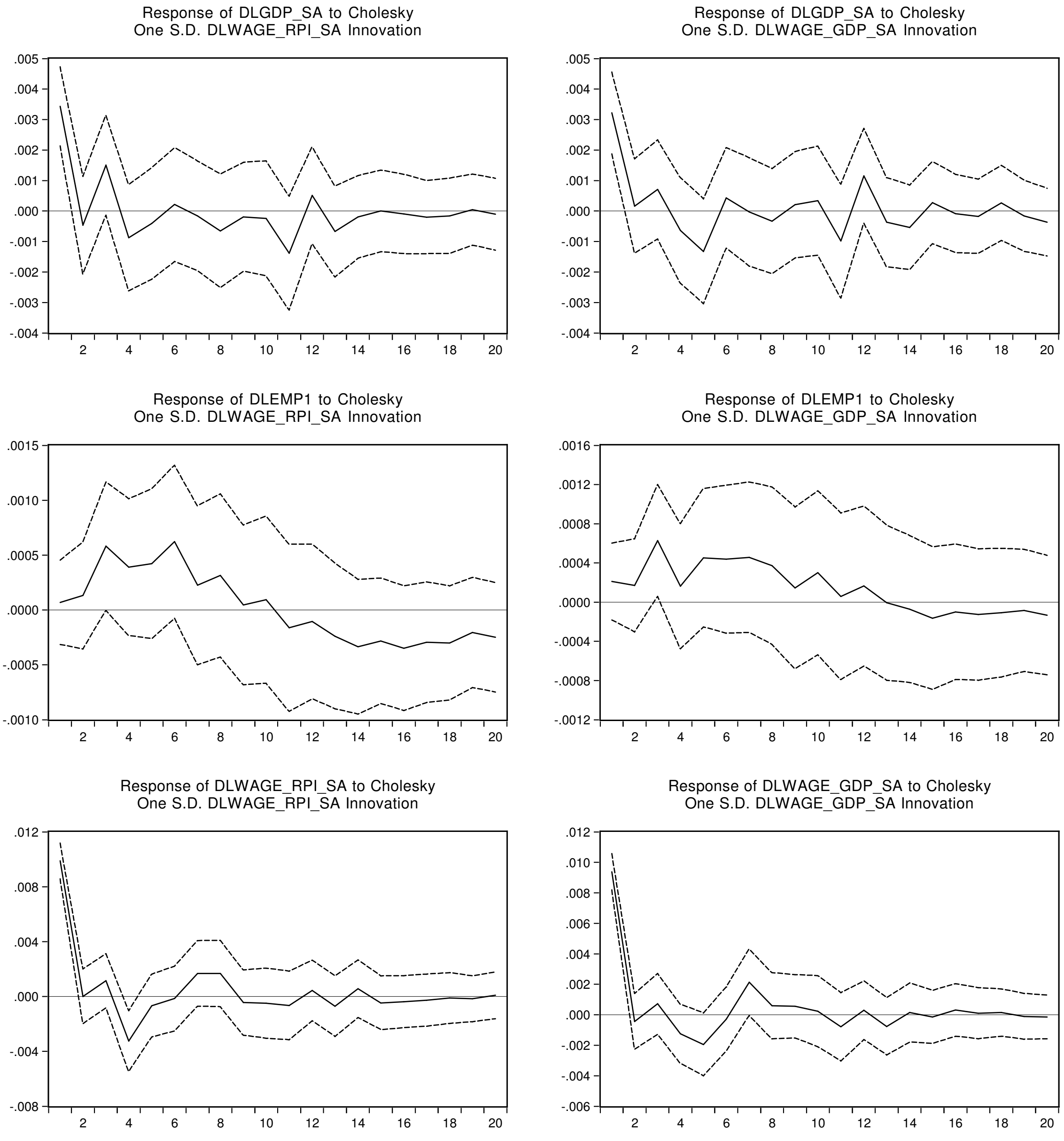

Figure 6: Impulse response functions of GDP (top), employment (middle), earnings (bottom), to a positive real earnings shock, VARs with SA real GDP, SA real earnings, and SA total employment (one quarter log differences). Left panel: RPI deflated earnings, right panel: GDP deflated earnings.

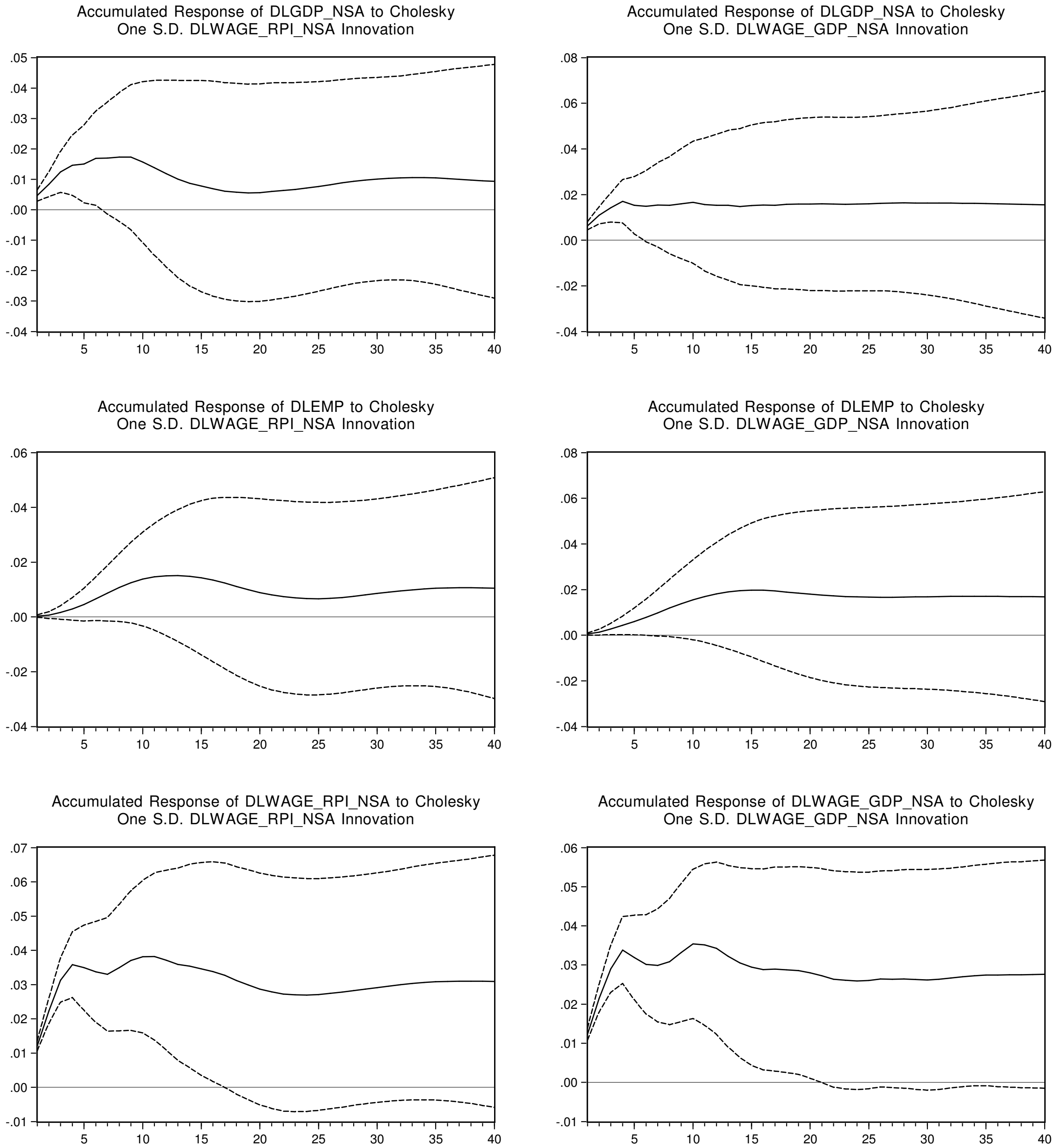

Figure 7: Accumulated impulse response functions of GDP (top), employment (middle), earnings (bottom), to a positive real earnings shock, VARs with NSA real GDP, NSA real earnings, and SA total employment (four quarter log differences). Left panel: RPI deflated earnings, right panel: GDP deflated earnings.

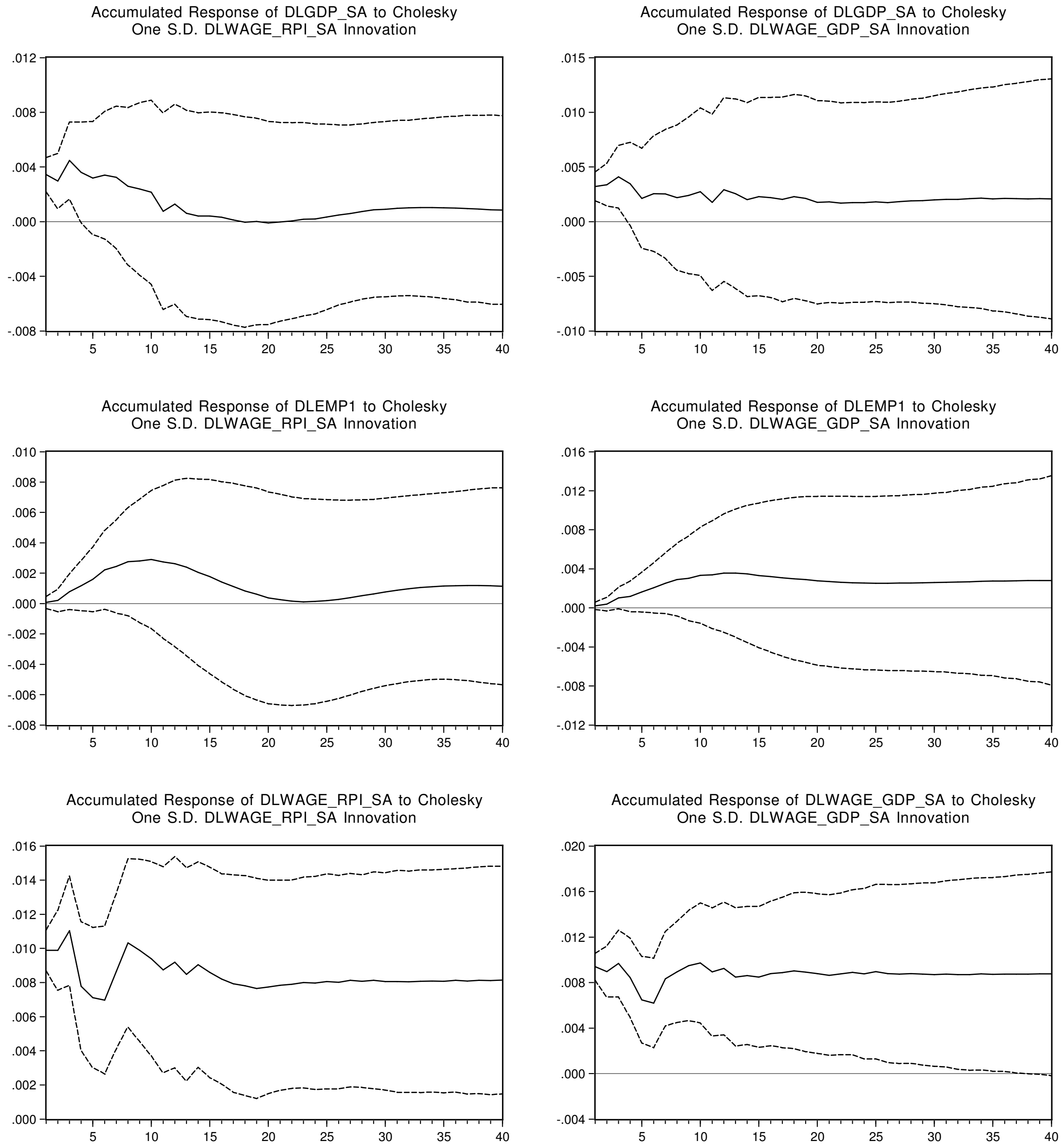

Figure 8: Accumulated impulse response functions of GDP (top), employment (middle), earnings (bottom), to a positive real earnings shock, VARs with SA real GDP, SA real earnings, and SA total employment (one quarter log differences). Left panel: RPI deflated earnings, right panel: GDP deflated earnings.

Table 1: Forecast error variance decompositions[a]

Forecast Horizon	GDP	Employment	Earnings
VAR using RPI deflated earnings[b]			
1	18.15	1.09	100.00
2	16.90	0.94	99.37
4	15.89	3.47	98.42
8	14.13	10.76	84.21
100	16.39	14.48	72.61
VAR using GDP deflated earnings[b]			
1	31.49	3.74	100.00
2	28.72	4.39	97.84
4	21.53	6.85	97.34
8	18.92	11.50	92.51
100	17.41	13.22	84.28

Notes: [a]We show the results of GDP, employment, and real earnings to shocks in real earnings for the VAR using NSA data; [b]Percentage points are shown.

exogenous increase in real earnings. As total employment does not respond significantly to real earnings shocks in figures 5 and 6, and the response of real earnings is uniformly greater than the response of aggregate demand, then we can say with confidence that both aggregate demand and the labour share increase in response to a real earnings shock in the United Kingdom. At the mean, from figures 5 and 6, our results indicate that a 1% shock to real earnings should increase the labour share by approximately 0.5% to 0.7%, and GDP by approximately 0.3% to 0.5%. At the lower end of our 95% confidence bands, our results indicate that a 1% shock to real earnings should increase the labour share by approximately 0.75% to 0.8%, and GDP by approximately 0.2% to 0.25%. Given this, we conclude that the data are consistent with the wage led aggregate demand hypothesis. However, the positive effect of a real earnings shock on GDP appears to be short lived. Figures 7 and 8 plots the cumulated counterparts to the impulse response functions presented in figures 5 and 6. One can observe that the permanent effects of a real earnings shock on GDP and employment are positive but relatively small, and at the 5% level are not significantly different from zero. Thus our results indicate that wage led aggregate demand effects operate at relatively high frequencies.

Finally, it was noted in section 4 that the labour share is counter-cyclical, despite the result that identified shocks to real earnings increase both GDP and the labour share. This implies that shocks to real earnings cannot account for a significant proportion of GDP movements, which is confirmed by the forecast error variance decompositions in table 1 for the VAR models with NSA real GDP, NSA real earnings, and SA total employment (the decompositions for the models with SA real GDP, SA real earnings, and SA total employment are similar). From this table we can see that higher proportions of the variation in GDP can be explained by real earnings shocks when using the GDP deflator, and that shocks to real earnings explain at most 31.49% of the variation in GDP, corresponding to the first lag of the forecast horizon when the VAR is estimated using GDP deflated earnings. In the long run, real earnings shocks explain less than 20% of the variation in GDP and total employment. These results support our previous conjecture that shocks to real earnings explain a relatively small proportion of the variance in GDP. Therefore, while positive real earnings shocks result in an increase in both GDP and the labour share, these shocks do not account for a large proportion of GDP movements, such that the observed labour share in the UK is countercyclical.

6 Concluding Remarks

This paper starts with the observation that the wage led aggregate demand hypothesis has been tested in the UK using a variety of estimation procedures. Studies relying on equation-by-equation estimation procedures tend to find support for wage led aggregate demand in the UK, while the single study using systems estimation finds no support for the hypothesis. In order to resolve this incongruity, we test the wage led aggregate demand hypothesis using VAR models estimated on quarterly data. We use a variety of data types, and take a relatively liberal approach to identification. Particularly, we use a simple partial identification strategy based on shocks to real earnings rather than the labour share. Our conclusions are unambiguous: all of our models indicate that positive shocks to real earnings increase both GDP and the labour share, indicating that aggregate demand in the UK is wage led. Thus our investigation provides support for the wage led aggregate demand hypothesis in the UK during the period of study.

We believe the implications for heterodox theory are the following. First, a Goodwinian (profit-led) interpretation of the Bhaduri-Marglin model is not supported, and nor is the production side of the standard Goodwin model. However, it is reasonable to conjecture that Goodwin effects might operate over the medium to long run, following Atkinson (1969), as we only find evidence for expansionary real earnings shocks in the short run. From the perspective of policy, it would seem possible in principle for the government to use an incomes policy for the purpose of demand management, as opposed to price control as was the case in the 1960s and 1970s. However, it should be noted that the expansionary effects of higher earnings seem to be quite limited and relatively short-lived by our estimates, and that there is very little impact on total employment.

One possible avenue for future research is to take a more expansive approach to the effects of wage shocks on the major macroeconomic variables. This will require a treatment of nominal wage and price inflation, which we do not provide in the present paper. A second is to explore the link between employment and the labour share in more detail, which might be amenable to direct estimation. A third possibility is to exploit the existence of long time series data at annual frequency for countries such as the UK. Finally, one could estimate non-linear models to investigate the effects of earnings or wage shocks at different stages of the business cycle. One hopes, with the ongoing work in this area, that a consensus will be reached on the broad effects of income distribution on aggregate demand in the near future.

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A Unit root tests

Table A1: Linear unit root tests on seasonally adjusted data

	ADF[a,b]	DF-GLS[a,b]	M-PP[a,b]
Log-levels			
GDP	-3.36*	-2.84*	-19.84**
Employment	-1.91	-2.36	-8.19
Earnings (RPI deflator)	-1.62	-1.89	-7.05
Earnings (GDP deflator)	-3.77**	-2.54	-9.84
First differences of the log-levels			
GDP	-5.46**	-3.87**	-25.36***
Employment	-3.08	-3.19**	-18.25**
Earnings (RPI deflator)	-4.11***	-5.58***	-48.70**
Earnings (GDP deflator)	-3.73**	-11.89***	-68.75***

Notes: [a]Statistics reported: ADF and DF-GLS=t-statistic; M-PP=MZa-statistic; [b]Critical values used: ADF=MacKinnon (1996) one-sided p-values; DF-GLS=Table 1 of Elliot et al. (1996); M-PP=Table 1 of Ng and Perron (2001). *, **, and *** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

Table A2: HEGY tests on non-seasonally adjusted data

	$\pi_1 = 0$[a]	$\pi_2 = 0$[a]	$\pi_3 = \pi_4 = 0$[a]
Log-levels			
GDP	-2.54	-0.94	3.07
Earnings (RPI deflator)	1.57	0.01	0.02
Earnings (GDP deflator)	-3.61**	-0.62	1.70
Four-quarter differences of the log-levels			
GDP	-4.08***	-6.21***	49.34***
Employment	-3.31*	-4.26***	33.14***
Earnings (RPI deflator)	-4.49***	-3.86***	32.86***
Earnings (GDP deflator)	-4.76***	-3.84***	25.29***

Notes: [a]P-values were obtained from Monte Carlo simulations (2000 replications). Lag length selected according to the Akaike information criterion. *, **, and *** respectively denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels.

B Joint misspecification tests

Table B1: Misspecification tests over VAR models with NSA data[a]

Autocorrelation[b]		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
VAR using RPI deflated earnings					
16.79	0.052	396.93	0.09	95.31	0
VAR using GDP deflated earnings					
12.74	0.17	289.34	0.99	42.00	0

Notes: [a]Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Cholesky of covariance (Lutkepohl); [b]We only report the results that test for first-order serial correlation.

Table B2: Misspecification tests over VAR models with SA data[a]

Autocorrelation[b]		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
VAR using RPI deflated earnings					
7.45	0.59	426.42	0.009	30.79	0
VAR using GDP deflated earnings					
8.32	0.50	367.81	0.38	31.63	0

Notes: [a]Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Cholesky of covariance (Lutkepohl); [b]We only report the results that test for first-order serial correlation.