An empirical analysis of the profit squeeze theory for the USA and UK*

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Abstract

The profit squeeze theory of business cycles is examined, using annual data for the USA and UK spanning the period 1960 - 2015. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), Granger non-causality is tested between the unemployment rate and labour share, and the unemployment rate and profit rate, with and without gross domestic product as an auxiliary variable. The evidence presented does not appear to be consistent with a strong profit squeeze mechanism in the USA and UK during the period of study.

Keywords: Profit squeeze, Goodwin model, Business cycles.

JEL Codes: #, #, #, #.

*I would like to thank . . . Any remaining errors are the responsibility of the author.

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1 Introduction

This paper examines the profit squeeze theory of business cycles, using annual data for the USA and UK spanning the period 1960 - 2015. The profit squeeze theory descends from passages in the first volume of *Capital*, where Marx argues that wages, and by extension profits, are regulated by the expansions and contractions of unemployment which constitute the business cycle. Thus,

> "The course characteristic of modern industry, viz., a decennial cycle (interrupted by smaller oscillations), of periods of average activity, production at high pressure, crisis and stagnation, depends on the constant formation, the greater or less absorption, and the re-formation of the industrial reserve army or surplus-population . . . Taking them as a whole, the general movements of wages are exclusively regulated by the expansion and contraction of the industrial reserve army, and these again correspond to the periodic changes of the industrial cycle." (Marx, 2003 [1867]: 592-596).

The theory hinted at in these passages was formalised by Goodwin in 1967. In the Goodwin model, falling unemployment leads to an increase in the share of income going to labour, via a real wage Phillips curve. As profitability declines, accumulation declines, which leads to an increase in unemployment as a recession sets in. Eventually, rising unemployment leads to a decrease in the share of income going to labour, a recovery in profits, and a consequent increase in accumulation.

The profit squeeze theory of business cycles has been examined empirically in a number of papers. Harvie (2000) and Mohun and Veneziani (2006) find qualitative support for the profit squeeze theory, and Goldstein (1999), Barbosa-Filho and Taylor (2006), Tarassow (2010), Basu et al (2013), and Rada and Kiefer (2016) find differing levels of quantitative support using multivariate time series methods. The approach pursued in the present paper is closely related to Tarassow (2010) and Basu et al (2013), as VAR models are used to analyse the data. Where these papers use pre-filtered quarterly data and focus on short run effects, Rada and Kiefer (2016) focus on the long run decline in the labour share in OECD countries.

The validity of pre-filtering non-stationary or nearly non-stationary time series for the purposes of statistical inference is disputed. Cogley and Nelson (1995) argue that the Hodrick-Prescott filter, for example, can lead to artificial business cycle dynamics. On the other hand, Ravn and Uhlig (2002) observe that, "the HP-filter has withstood the test of time and the fire of discussion remarkably well", and it continues to be widely used in macroeconometrics. The validity of cointegration analysis and vector error correction models is less disputed, but it is well known that any errors in unit root and cointegration tests, both of which tend to have low power, can lead to serious biases in subsequent inference. See, for example, Swanson et al (2003) and Gospodinov et al (2013).

An alternative to pre-filtering and cointegration analysis is to work with the raw data in levels, and particularly to estimate and analyse unrestricted VAR models in levels. In this case, certain tests (e.g. t-tests on individual parameters) are generally valid, whilst other tests are invalid. An example of the latter is the standard Wald test for Granger non-causality. However, Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) demonstrate that a simple adjustment to the Granger non-causality test renders the inference standard. As a result, the causality structure of a multivariate time series process can be studied without the need for filtering or pre-tests for cointegration.

The present paper tests the profit squeeze theory on the USA and UK using the method for testing Granger non-causality suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). As such, the paper is intended as complement to Tarassow (2010), Basu et al (2013), and Rada and Kiefer (2016). Using this method, the evidence presented is not unambiguously consistent with a strong profit squeeze mechanism in the USA and UK during the period of study. In particular, when the log level or log difference of real GDP is controlled for, neither the labour share nor the rate of profit appear to have significant predictive capacity for the unemployment rate in the USA and UK during the period of study.

The rest of the paper is organised as follows. Section 2 discusses the empirical approach used in the present paper, and section 3 discusses the data sources and characteristics. Section 4 presents the results, and section 5 concludes.

2 Empirical approach

2.1 VAR models

In order to examine the profit squeeze theory, VAR models are utilised. First, VARs are estimated in the unemployment rate and labour share, and the unemployment rate and profit rate. Second, VARs are estimated in the unemployment rate, labour share, and the log of real GDP, and the unemployment rate, profit rate, and the log of real GDP. In total, therefore, four VAR models are estimated for each country. Denoting the unemployment rate by u, the labour share by ω, the profit rate by π, the log of real GDP by y, and a general vector of endogenous variables by z, the models are,

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

where ϵ_t is a white noise vector process with $\epsilon_t \sim IID(0, \Sigma)$, and the vector z_t is $[u_t, \omega_t]'$, $[u_t, \pi_t]'$, $[u_t, \omega_t, y_t]'$, or $[u_t, \pi_t, y_t]'$.

In order to make the profit squeeze theory operational, Granger non-causality tests are employed. Granger non-causality in a VAR setting is equivalent to zero restrictions on the parameter matrices A_i. Suppose, for example, that a VAR in the unemployment rate and labour share has been estimated, so $z_t = [u_t, \omega_t]'$. In this case, the labour share is Granger non-causal (GNC) for the unemployment rate if the element in the first row, second column of each A_i is equal to zero. Likewise, the unemployment rate is GNC for the labour share if the element in the second row, first column of each A_i is equal to zero. Granger causality is therefore the most straightforward way of rendering the requirements of the profit squeeze theory operational in VAR models, given the signs of the point estimates agreeing with theory.

If the various point estimates agree with the profit squeeze theory and are jointly significant (i.e. Granger non-causality can be rejected at conventional confidence levels), then the theory will be considered consistent with the data. Note that this method does not constitute a test of the profit squeeze theory. Indeed, there does not appear to be a formulation of the profit squeeze theory that is amenable to testing, and the widely cited Goodwin model is too "starkly schematized" to be a useful representation of the data (Goodwin 1967, Harvey 2000). Instead, the method is closer to the "data reduction" approaches of Spanos (1995) or Hendry (1995), where propositions from economic theory are compared to valid representations of the data.

2.2 Granger causality in the bivariate VAR models

It is often useful to represent Granger causality patterns as a directed graph, where a directed edge from a node a to a node b corresponds to Granger causality from a variable a to a variable b (Giles 2002). In light of the discussions in sections 1 and 2.1, in the VAR with $z_t = [u_t, \omega_t]$, the profit squeeze theory will be considered consistent with the data if the signs of the point estimates agree with theory, and the following pattern of Granger causality is supported:

$$\begin{tikzcd} u \arrow[r, bend left] & \omega \arrow[l, bend left] \end{tikzcd}$$

In this case, the unemployment rate is GC for the labour share, and the labour share is GC for the unemployment rate. The profit squeeze theory will be therefore be considered inconsistent with the data if at least one of the following individual null hypotheses cannot be rejected at conventional confidence levels:

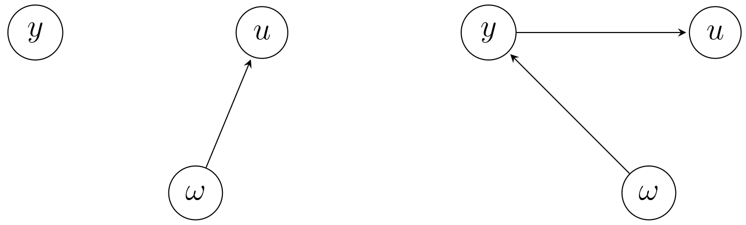
- H_{01}: u is GNC for ω (against the alternative, H_{11}: u is GC for ω).
- H_{02}: ω is GNC for u (against the alternative, H_{12}: ω is GC for u).

In the VARs with $z_t = [u_t, \pi_t]$, the profit squeeze theory is supported if the unemployment rate is GC for the profit rate, and the profit rate is GC for the unemployment rate. Therefore, the foregoing directly applies, where the labour share is replaced with the profit rate.

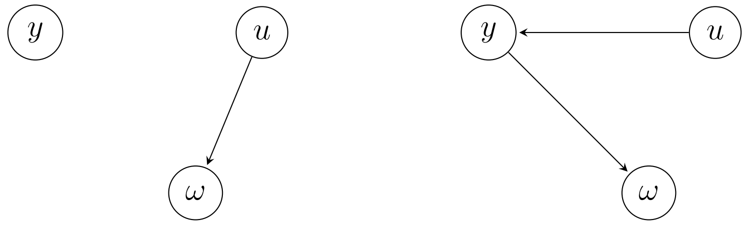
2.3 Granger causality in the trivariate VAR models

In bivariate VARs, if Granger non-causality cannot be rejected from a variable a to a variable b, then the variable a has no predictive capacity for the variable b at any horizon. However, in a VAR with more than two variables this ceases to be the case. For example, it is possible that a variable a is GNC for b, but GC for a third variable c. If c is GC for b, then a has predictive capacity for b two periods ahead (despite the fact that it has no predictive capacity one period ahead). This type of multi-step Granger causality is explored in detail in Dufour and Renault (1998).

As in the bivariate VARs, therefore, the profit squeeze theory is consistent with the data if bi-directional Granger causality exists between the labour share and unemployment rate. However, Granger causality can now run indirectly via GDP. In this case, the labour share is GC for the unemployment rate if at least one of the following patterns holds:



In the left pattern, the labour share is directly GC for the unemployment rate. In the right pattern, the labour share is directly GC for GDP, and GDP is directly GC for the unemployment rate, hence the labour share is indirectly GC for the unemployment rate. Similarly, the unemployment rate is GC for the labour share if at least one of the following patterns holds:



In the left pattern, the unemployment rate is directly GC for the labour share. In the right pattern, the unemployment rate is directly GC for GDP, and GDP is directly GC for the labour share, hence the unemployment rate is indirectly GC for the labour share.

Giles (2002), building on the work of Dufour and Renault (1998), demonstrates that neither direct nor indirect GNC from the labour share to the unemployment rate can be rejected if and only if at least one of the following individual null hypotheses cannot be rejected:

- H_{03}: ω is GNC for u and ω is GNC for y (against the alternative, H_{13}: ω is GC for u or ω is GC for y).
- H_{04}: ω is GNC for u and y is GNC for u (against the alternative, H_{14}: ω is GC for u or y is GC for u).

Failure to reject at least one of these hypotheses implies that we cannot reject direct Granger non-causality from the labour share to the unemployment rate and we cannot reject indirect Granger non-causality from the labour share to the unemployment rate via GDP. Similarly, neither direct nor indirect GNC from the unemployment rate to the labour share can be rejected if and only if at least one of the following individual null hypotheses cannot be rejected:

- H_{05}: u is GNC for ω and u is GNC for y (against the alternative, H_{15}: u is GC for ω or u is GC for y).
- H_{06}: u is GNC for ω and y is GNC for ω (against the alternative, H_{16}: u is GC for ω or y is GC for ω).

Given the above, the profit squeeze theory will be considered inconsistent with the data if at least one of the foregoing individual null hypotheses, H_{03} - H_{06}, cannot be rejected at conventional confidence levels. As in the bivariate VARs, in the VARs with $z_t = [u_t, \pi_t, y_t]$, the foregoing directly applies, where the labour share is replaced with the profit rate.

2.4 The Toda-Yamamoto and Dolado-Lütkepohl method

As noted in the introduction, in order to keep the investigation as transparent as possible, none of the data are pre-filtered. However, given the results of 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), summarised in appendix A, we cannot reject the existence of unit roots in each of the data series employed. Standard inference in Granger non-causality tests is therefore invalid, as the Wald test statistics do not follow the usual distribution. One option is to test for cointegration, and conduct Granger non-causality tests in the transformed model that takes the results of the cointegration tests into account. However, pre-testing for unit roots and cointegration can cause severe pre-test bias in the subsequent Granger non-causality tests, as unit root and cointegration tests have low power.

An alternative approach, suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), is to estimate the relevant VAR in levels, and conduct Granger non-causality tests on the VAR model re-estimated with a superfluous lag. The two papers demonstrate that Wald statistics follow the usual distribution when a superfluous lag is added to the model, as long as none of the parameters on the superfluous lag variables are restricted. Essentially, this method avoids the pre-test bias generated by unit root and cointegration tests at the expense of a reduction in efficiency caused by the superfluous lag. As the present study is concerned solely with patterns of causality, rather than long-run relations, the superfluous lag approach of Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) is used.

3 Data

All data is annual, spanning the period 1960 - 2015, and is taken from the AMECO database. Annual data is used for two reasons. First, quarterly data for UK unemployment is only available after 1992; prior to this, all quarterly Labour Force Survey data is interpolated between annual observations. Second, annual data avoids the need for seasonal adjustment. The labour share series is the AMECO adjusted labour share at market prices (ALCD0). The unemployment rate series is the AMECO civilian unemployment rate (ZUTN). The profit rate series is the AMECO net return on net capital stock (APNDK). The GDP series is the AMECO gross domestic product at 2010 reference level (OVGD).

Figures 1 and 2 plot the labour share, profit rate, and unemployment rate series for the USA and UK, respectively. As well as the labour share at market prices, the labour share at factor cost (AMECO code ALCD2) is also plotted for each country. From this it is obvious that the labour share series at market prices and factor cost are very similar, with the only noticeable difference being a level shift. For this reason, the choice of labour share series is not expected to materially affect the results.

From figures 1 and 2, the difference in fortunes of workers in the USA and UK during the last 4 decades is immediately apparent. In the USA, the unemployment rate did not fall below 3% at any point in the sample, and fluctuated around an average level of approximately 6%. In contrast, the unemployment rates in the UK remained below 3% until the early 1970s, at which point it experienced a rapid increase. By the middle of the 1980s in the UK, the

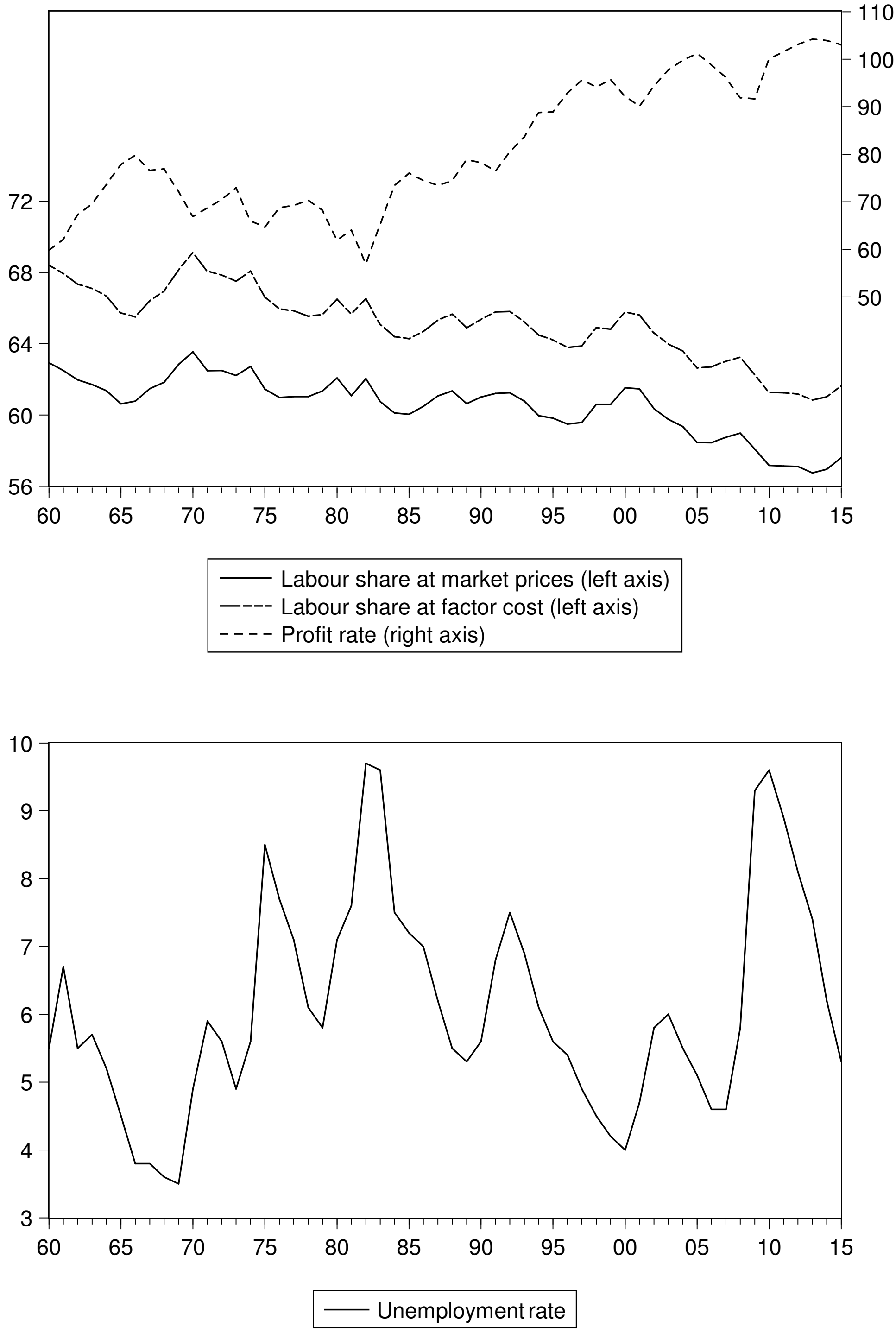


Figure 1: USA labour share, profit rate, and unemployment rate series, 1960 - 2015.

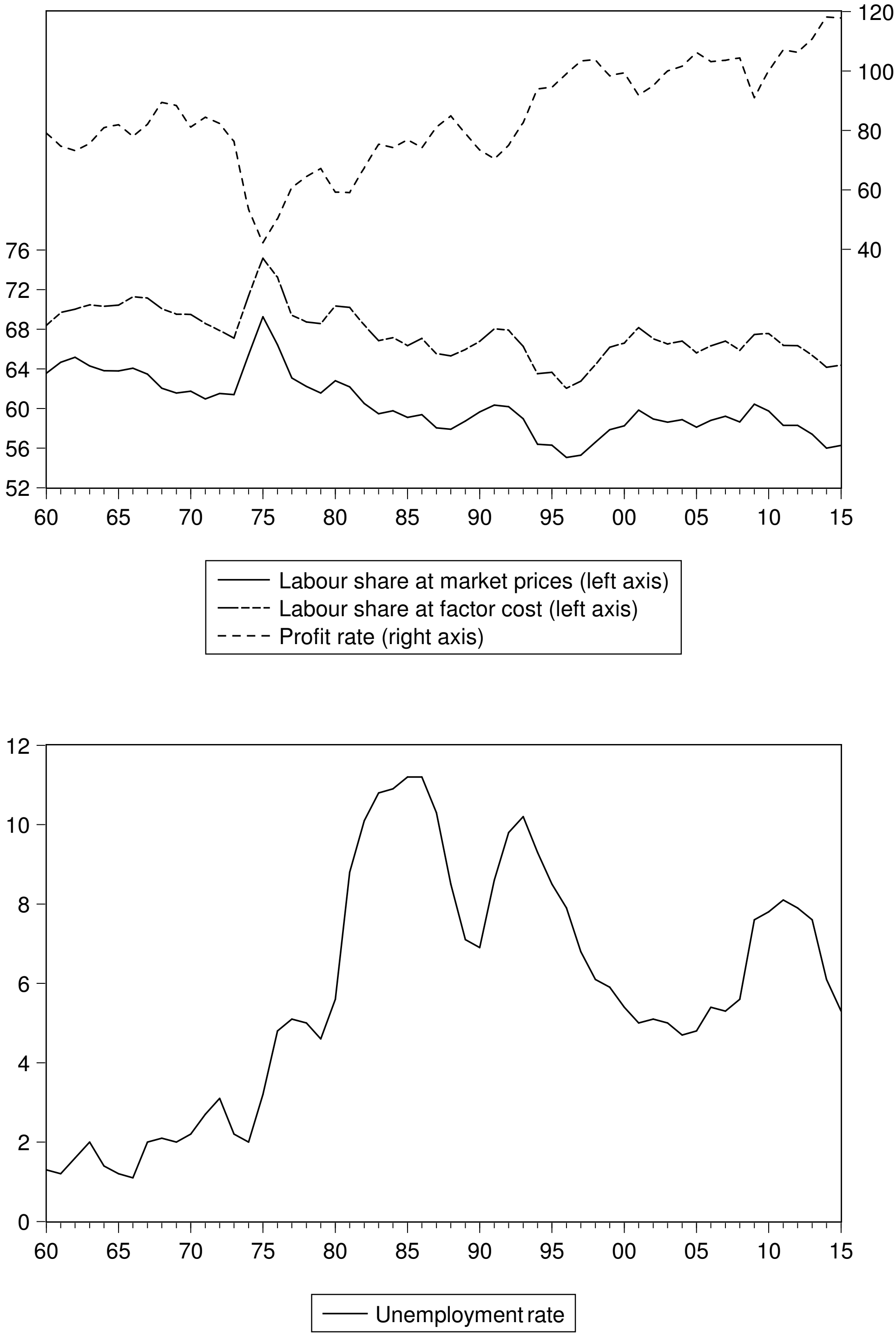


Figure 2: UK labour share, profit rate, and unemployment rate series, 1960 - 2015.

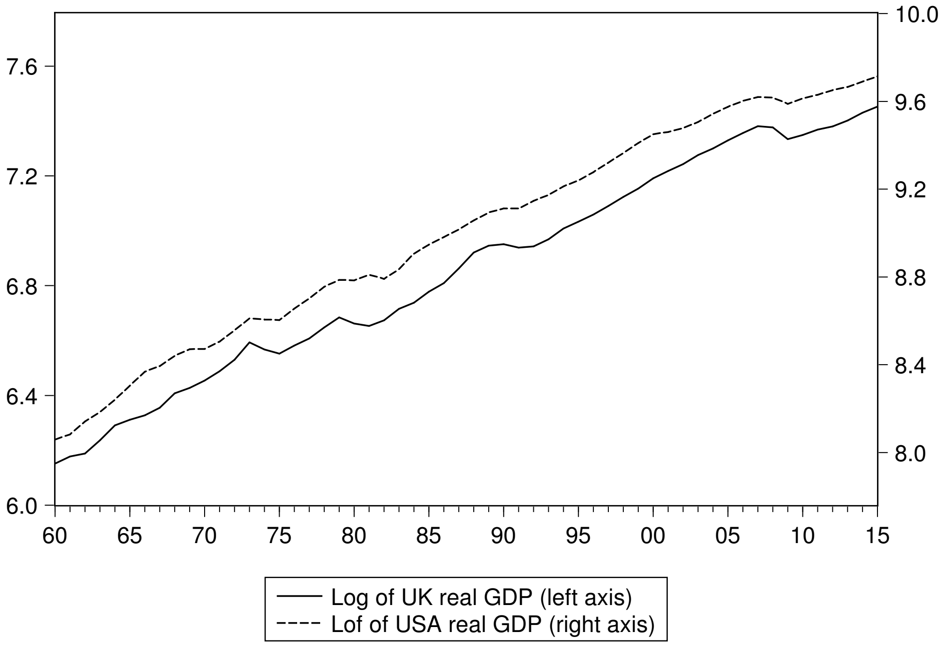


Figure 3: USA and UK GDP series, 1960 - 2015.

unemployment rate exceeded 10%, and while it subsequently reduced relative to this level, the unemployment rate remains elevated compared levels seen in the 1960s.

In the USA and UK, the labour share has steady declined since the mid to late 1970s, and the profit rate has steadily increased over the same period, reflecting a sustained increase in household inequality over the same period. Note that the AMECO profit rate series is an index, equal to 100 in 2010. Finally, figure 3 plots the log of real GDP for the USA and UK. From this figure, the major recessions in the sample period are immediately apparent, as is the general similarity in the behaviour of real GDP in the two countries over time.

4 Results

4.1 USA

4.1.1 VAR in unemployment rate and labour share

For the VAR in the unemployment rate and labour share (USA data), the Akaike information criterion (AIC) and the Schwartz information criterion (SIC) suggest two lags and one lag, respectively. Autocorrelation problems exist in the model with one lag, however, so the model is estimated with two lags. The estimated model is summarised in box 1, where all point estimates, test statistics, and p-values are rounded to two decimal places. There appear to be non-normality issues, but no heteroskedasticity. The estimated signs agree with theory, and the trend coefficient is statistically significant in the labour share equation. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl

Point estimates:

$$\begin{bmatrix} u_t \\ \omega_t \end{bmatrix} = \begin{bmatrix} -9.46 \\ 14.40 \end{bmatrix} + \begin{bmatrix} 0.02 \\ -0.02 \end{bmatrix} t + \begin{bmatrix} 1.13 & 0.47 \\ -0.27 & 0.83 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \omega_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} -0.35 & -0.30 \\ 0.15 & -0.05 \end{bmatrix} \begin{bmatrix} u_{t-2} \\ \omega_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{ut} \\ \epsilon_{\omega t} \end{bmatrix}.$$

Misspecification tests:

Autocorrelation		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
3.32	0.51	19.91	0.92	33.25	0.00

Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Doornik-Hansen. Only first-order autocorrelation is reported.

Box 1: Estimation output for VAR in unemployment rate and labour share (USA data).

(1996), i.e. testing for Granger non-causality after estimation with a superfluous lag, the p-values for hypotheses H_{01} and H_{02} are,

- H_{01}: u is GNC for ω; $p = 0.0013$.
- H_{02}: ω is GNC for u; $p = 0.1974$.

Thus we can reject H_{01}: u is GNC for ω at the 1% level, but we cannot reject H_{02}: ω is GNC for u at conventional significance levels. On inspection of recursive estimates for the unemployment rate and labour share, some of the estimated parameters appear to suffer from instability over the period of study. This is mainly confined to the unemployment equation, where there is some evidence of a one-off shift in four of the six parameters after 2008. This instability is mitigated if we reduce the sample to 1960 - 2008, and is also mitigated to some extent if we remove the linear trend. However, the main reason, given the results presented in section 5.1.3, appears to be the exclusion of the log of real GDP in the model.

4.1.2 VAR in unemployment rate and profit rate

For the VAR in the unemployment rate and profit rate (USA data), the AIC and SIC both suggest two lags, and there are no autocorrelation problems for a model with two lags. As in the VAR in the unemployment rate and labour share, there appears to be non-normality but not heteroskedasticity. The estimated model is summarised in box 2. The estimated signs

Point estimates:

$$\begin{bmatrix} u_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} 6.5 \\ -8.3 \end{bmatrix} + \begin{bmatrix} 0.06 \\ -0.06 \end{bmatrix} t + \begin{bmatrix} 0.80 & -0.12 \\ 2.30 & 1.25 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \pi_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} -0.22 & 0.05 \\ -1.33 & -0.19 \end{bmatrix} \begin{bmatrix} u_{t-2} \\ \pi_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{ut} \\ \epsilon_{\pi t} \end{bmatrix}.$$

Misspecification tests:

Autocorrelation		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
6.20	0.18	30.92	0.42	15.38	0.00

Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Doornik-Hansen. Only first-order autocorrelation is reported.

Box 2: Estimation output for VAR in unemployment rate and profit rate (USA data).

agree with theory, and the trend coefficient is statistically significant in the unemployment rate equation. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), i.e. testing for Granger non-causality after estimation with a superfluous lag, the p-values for hypotheses H_{01} and H_{02} are,

- H_{01}: u is GNC for π; $p = 0.0003$.
- H_{02}: π is GNC for u; $p = 0.0045$.

Thus we can reject H_{01}: u is GNC for π at the 1% level, and we can reject H_{02}: π is GNC for u at the 1% level. On inspection of recursive estimates for the unemployment rate and profit rate, the estimated parameters appear to be relatively stable. There is, however, a degree of possible instability around 1979-1980 in some of the slope coefficients in both the unemployment rate and profit rate equations. Despite this, the estimations appear to be consistent with the profit squeeze theory.

4.1.3 VAR in unemployment rate, labour share, and GDP

For the VAR in the unemployment rate, labour share, and log real GDP (USA data), the AIC and the SIC suggest two lags and one lag, respectively. Autocorrelation problems exist in the model with one lag, however, so the model is estimated with two lags. The model with two lags does not suffer from heteroskedasticity, but does suffer from non-normality. The estimated model is summarised in box 3. A number of the estimated partial effects

Point estimates:

$$\begin{bmatrix} u_t \\ \omega_t \\ y_t \end{bmatrix} = \begin{bmatrix} -48.96 \\ -15.47 \\ 0.96 \end{bmatrix} + \begin{bmatrix} -0.20 \\ -0.18 \\ 0.00 \end{bmatrix} t + \begin{bmatrix} 0.47 & -0.06 & -37.60 \\ 0.04 & 0.83 & 15.84 \\ 0.01 & 0.00 & 1.66 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \omega_{t-1} \\ y_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} 0.31 & 0.09 & 43.76 \\ -0.09 & -0.22 & -10.93 \\ -0.01 & -0.00 & -0.80 \end{bmatrix} \begin{bmatrix} u_{t-2} \\ \omega_{t-2} \\ y_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{ut} \\ \epsilon_{\omega t} \\ \epsilon_{yt} \end{bmatrix}.$$

Misspecification tests:

Autocorrelation		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
10.66	0.30	76.51	0.71	21.20	0.00

Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Doornik-Hansen. Only first-order autocorrelation is reported.

Box 3: Estimation output for VAR in unemployment rate, labour share, and GDP (USA data).

are very small, and a number of the signs disagree with the profit squeeze theory[1]. The trend coefficient is significant in the labour share equation. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), i.e. testing for Granger non-causality after estimation with a superfluous lag, the p-values for hypotheses H_{03} - H_{06} are,

- H_{03}: ω is GNC for u and ω is GNC for y; $p = 0.9831$.
- H_{04}: ω is GNC for u and y is GNC for u; $p = 0.0196$.
- H_{05}: u is GNC for ω and u is GNC for y; $p = 0.2832$.
- H_{06}: u is GNC for ω and y is GNC for ω; $p = 0.0000$.

Thus we cannot reject H_{03}: ω is GNC for u and ω is GNC for y at conventional confidence levels, and we cannot reject H_{05}: u is GNC for ω and u is GNC for y at conventional confidence levels. However, we can reject H_{04}: ω is GNC for u and y is GNC for u at the

[1]Note that the partial effect of the first lag of log real GDP on the unemployment rate of -37.6 implies that a one percent increase in real GDP should reduced the unemployment rate by approximately 0.376 percentage points, *ceteris paribus*. Likewise, the partial effect of the first lag of log real GDP on the labour share of 15.84 implies that a one percent increase in real GDP should increase the labour share by approximately 0.1584 percentage points, *ceteris paribus*.

Point estimates:

$$\begin{bmatrix} u_t \\ \pi_t \\ y_t \end{bmatrix} = \begin{bmatrix} 1.81 \\ 135.11 \\ 0.05 \end{bmatrix} + \begin{bmatrix} 0.20 \\ 0.51 \\ -0.00 \end{bmatrix} t + \begin{bmatrix} 0.31 & -0.02 & -34.02 \\ 1.41 & 1.29 & -40.03 \\ 0.01 & 0.00 & 1.55 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \pi_{t-1} \\ y_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} 0.16 & -0.05 & 34.85 \\ -1.12 & -0.34 & 23.72 \\ -0.01 & 0.00 & -0.57 \end{bmatrix} \begin{bmatrix} u_{t-2} \\ \pi_{t-2} \\ y_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{ut} \\ \epsilon_{\omega t} \\ \epsilon_{yt} \end{bmatrix}.$$

Misspecification tests:

Autocorrelation		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
16.87	0.051	91.67	0.27	16.27	0.01

Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Doornik-Hansen. Only first-order autocorrelation is reported.

Box 4: Estimation output for VAR in unemployment rate, profit rate, and GDP (USA data).

5% level, and we can reject H_{06}: u is GNC for ω and y is GNC for ω at the 1% level. Therefore, we conclude that the data do not support the profit squeeze theory of business cycles using the VAR model in the unemployment rate, labour share, and log real GDP (USA data). Instead, the data suggests that log real GDP is GC for unemployment and the labour share, with no other Granger causality. The joint restrictions that imply this pattern cannot be rejected at conventional significance levels ($p = 0.6996$), and all of the recursive estimates appear to be stable when these joint restrictions are imposed. This suggests that the inference is valid. In contrast, although the recursive parameter estimates are stable in the labour share equation when the restrictions are not imposed, there is still a degree of instability around 1990 in the GDP and unemployment equations in the unconstrained model.

4.1.4 VAR in unemployment rate, profit rate, and GDP

For the VAR in the unemployment rate, profit rate, and log real GDP (USA data), the AIC and the SIC suggest two lags and one lag, respectively. Autocorrelation problems exist in the model with one lag, however, so the model is estimated with two lags. The model with two lags does not suffer from heteroskedasticity, but does suffer from non-normality. The estimated model is summarised in box 4. A number of the estimated partial effects are very small, although in general the signs are as expected. The trend coefficient is insignificant in each equation. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), i.e. testing for Granger non-causality after estimation with a superfluous lag, the p-values for hypotheses H_{03} - H_{06} are,

- H_{03}: π is GNC for u and π is GNC for y; $p = 0.5261$.
- H_{04}: π is GNC for u and y is GNC for u; $p = 0.0009$.
- H_{05}: u is GNC for π and u is GNC for y; $p = 0.1213$.
- H_{06}: u is GNC for π and y is GNC for π; $p = 0.0374$.

Thus we cannot reject H_{03}: π is GNC for u and π is GNC for y at conventional confidence levels, and we cannot reject H_{05}: u is GNC for π and u is GNC for y at conventional confidence levels. However, we can reject H_{04}: π is GNC for u and y is GNC for u at the 1% level, and we can reject H_{06}: u is GNC for π and y is GNC for π at the 5% level. Therefore, we conclude that the data do not support the profit squeeze theory of business cycles using the VAR model in the unemployment rate, profit rate, and log real GDP (USA data). There is no obvious pattern of Granger causality suggested by the data, but the recursive estimates are relatively stable in the profit rate and GDP equations in the unconstrained model. The unemployment equation appears to suffer from a degree of instability, but this is mitigated if we impose π GNC for u.

4.2 UK

4.2.1 VAR in unemployment rate and labour share

For the VAR in the unemployment rate and labour share (UK data), the AIC and the SIC both suggest two lags. No autocorrelation problems exist in the model with two lags, and the model does not appear to suffer from heteroskedasticity. However, there does appear to be an issue of non-normality. The estimated model is summarised in box 5, where all estimates are rounded to two decimal places. The estimated signs agree with theory, and the trend coefficient is statistically significant in the labour share equation at the 10% level. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), i.e. testing for Granger non-causality after estimation with a superfluous lag, the p-values for hypotheses H_{01} and H_{02} are,

- H_{01}: u is GNC for ω; $p = 0.0489$.
- H_{02}: ω is GNC for u; $p = 0.0756$.

Thus we can reject H_{01}: u is GNC for ω at the 5% level, and we can reject H_{02}: ω is GNC for u at the 10% level. On inspection of recursive estimates for the unemployment rate and labour share, the estimated parameters are relatively stable, particularly in the unemployment rate equation. The appears to be a small amount of instability in the coefficients on lagged unemployment in the labour share equation, but it is not as pronounced as the instability in the equivalent VAR using US data.

Point estimates:

$$\begin{bmatrix} u_t \\ \omega_t \end{bmatrix} = \begin{bmatrix} -3.98 \\ 19.52 \end{bmatrix} + \begin{bmatrix} 0.01 \\ -0.03 \end{bmatrix} t + \begin{bmatrix} 1.40 & 0.25 \\ -0.46 & 1.03 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \omega_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} -0.44 & -0.19 \\ 0.31 & -0.32 \end{bmatrix} \begin{bmatrix} u_{t-2} \\ \omega_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{ut} \\ \epsilon_{\omega t} \end{bmatrix},$$

Misspecification tests:

Autocorrelation		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
1.56	0.82	38.06	0.15	21.10	0.00

Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Doornik-Hansen. Only first-order autocorrelation is reported.

Box 5: Estimation output for VAR in unemployment rate and labour share (UK data).

4.2.2 VAR in unemployment rate and profit rate

For the VAR in the unemployment rate and profit rate (UK data), the AIC and SIC both suggest two lags, and there are no error autocorrelation problems for a model with two lags. The model does not appear to suffer from heteroskedasticity, but there does appear to be an issue of non-normality. The estimated model is summarised in box 6. The estimated signs agree with theory, and the trend coefficient is statistically significant in the unemployment rate equation. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), i.e. testing for Granger non-causality after estimation with a superfluous lag, the p-values for hypotheses H_{01} and H_{02} are,

- H_{01}: u is GNC for π; $p = 0.0057$.

- H_{02}: π is GNC for u; $p = 0.0198$.

Thus we can reject H_{01}: u is GNC for π at the 1% level, and we can reject H_{02}: π is GNC for u at the 5% level. As with the bivariate VAR in the unemployment rate and labour share, on inspection of recursive estimates for the unemployment rate and profit rate, some of the estimated parameters appear to suffer from instability over the period of study in the VAR model in the unemployment rate and profit rate (USA data). The instability is mitigated somewhat if we reduce the sample to 1960 - 2008, but there remains some evidence of instability in the profit rate equation around 1990. Again, the main reason for the instability, given the results presented in section 5.1.4, appears to be the exclusion of the log of real GDP in the model.

Point estimates:

$$\begin{bmatrix} u_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} 2.23 \\ -0.81 \end{bmatrix} + \begin{bmatrix} 0.03 \\ 0.05 \end{bmatrix} t + \begin{bmatrix} 1.26 & -0.05 \\ 3.70 & 1.24 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \pi_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} -0.37 & 0.03 \\ -3.39 & -0.26 \end{bmatrix} \begin{bmatrix} u_{t-2} \\ \pi_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{ut} \\ \epsilon_{\pi t} \end{bmatrix}.$$

Misspecification tests:

Autocorrelation		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
1.52	0.82	31.60	0.39	17.35	0.00

Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Doornik-Hansen. Only first-order autocorrelation is reported.

Box 6: Estimation output for VAR in unemployment rate and profit rate (UK data).

4.2.3 VAR in unemployment rate, labour share, and GDP

For the VAR in the unemployment rate, labour share, and log real GDP (UK data), the AIC and the SIC both suggest two lags. Autocorrelation problems do not exist exist in the model with two lags. Homoskedasticity can be rejected at the 5% level, but not at the 1% level, and the model suffers from non-normality. The estimated model is summarised in box 7. A number of the estimated partial effects are very small, and a number of the signs disagree with the profit squeeze theory. The trend coefficient is significant in all equations. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), i.e. testing for Granger non-causality after estimation with a superfluous lag, the p-values for hypotheses H_{03} - H_{06} are,

- H_{03}: ω is GNC for u and ω is GNC for y; $p = 0.5110$.
- H_{04}: ω is GNC for u and y is GNC for u; $p = 0.0033$.
- H_{05}: u is GNC for ω and u is GNC for y; $p = 0.2863$.
- H_{06}: u is GNC for ω and y is GNC for ω; $p = 0.0013$.

Thus we cannot reject H_{03}: ω is GNC for u and ω is GNC for y at conventional confidence levels, and we cannot reject H_{05}: u is GNC for ω and u is GNC for y at conventional confidence levels. However, we can reject H_{04}: ω is GNC for u and y is GNC for u at the 1% level, and we can reject H_{06}: u is GNC for ω and y is GNC for ω at the 1% level. Therefore,

Point estimates:

$$\begin{bmatrix} u_t \\ \omega_t \\ y_t \end{bmatrix} = \begin{bmatrix} -43.85 \\ -50.00 \\ 1.53 \end{bmatrix} + \begin{bmatrix} -0.17 \\ -0.30 \\ 0.01 \end{bmatrix} t + \begin{bmatrix} 1.11 & -0.02 & -23.66 \\ -0.51 & 0.89 & -4.00 \\ 0.01 & 0.00 & 1.49 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \omega_{t-1} \\ y_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} -0.12 & 0.07 & 30.48 \\ 0.41 & -0.16 & 15.04 \\ -0.01 & -0.00 & -0.72 \end{bmatrix} \begin{bmatrix} u_{t-2} \\ \omega_{t-2} \\ y_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{ut} \\ \epsilon_{\omega t} \\ \epsilon_{yt} \end{bmatrix}.$$

Misspecification tests:

Autocorrelation		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
6.37	0.70	112.32	0.02	15.34	0.02

Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Doornik-Hansen. Only first-order autocorrelation is reported.

Box 7: Estimation output for VAR in unemployment rate, labour share, and GDP (UK data).

we conclude that the data do not support the profit squeeze theory of business cycles using the VAR model in the unemployment rate, labour share, and log real GDP (UK data). Instead, the data suggests that log real GDP is GC for unemployment and the labour share, with no other Granger causality. The joint restrictions that imply this pattern cannot be rejected at conventional significance levels ($p = 0.4601$).

4.2.4 VAR in unemployment rate, profit rate, and GDP

For the VAR in the unemployment rate, profit rate, and log real GDP (UK data), the AIC and the SIC both suggest two lags. Autocorrelation problems do not exist exist in the model with two lags. Homoskedasticity can be rejected at the 5% level, but not at the 1% level, and the model does not appear to suffer from non-normality. The estimated model is summarised in box 8. A number of the estimated partial effects are very small, although in general the signs are as expected. The trend coefficient is insignificant in each equation. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), i.e. testing for Granger non-causality after estimation with a superfluous lag, the p-values for hypotheses H_{03} - H_{06} are,

- H_{03}: π is GNC for u and π is GNC for y; $p = 0.8555$.

Point estimates:

$$\begin{bmatrix} u_t \\ \pi_t \\ y_t \end{bmatrix} = \begin{bmatrix} -36.37 \\ 454.29 \\ 0.96 \end{bmatrix} + \begin{bmatrix} -0.15 \\ 1.90 \\ 0.00 \end{bmatrix} t + \begin{bmatrix} 1.06 & 0.01 & -25.44 \\ 2.33 & 1.08 & -42.78 \\ 0.01 & 0.00 & 1.38 \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \pi_{t-1} \\ y_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} -0.11 & -0.03 & 31.70 \\ -2.42 & -0.18 & -30.10 \\ -0.01 & 0.00 & -0.54 \end{bmatrix} \begin{bmatrix} u_{t-2} \\ \pi_{t-2} \\ y_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{ut} \\ \epsilon_{\omega t} \\ \epsilon_{yt} \end{bmatrix}.$$

Misspecification tests:

Autocorrelation		Heteroskedasticity		Normality	
Statistic	p-value	χ^2 statistic	p-value	Statistic	p-value
4.68	0.86	112.25	0.02	6.89	0.33

Tests employed: Serial correlation=Lagrange Multiplier; Heteroskedasticity=White (no cross terms); Normality=Doornik-Hansen. Only first-order autocorrelation is reported.

Box 8: Estimation output for VAR in unemployment rate, labour share, and GDP (UK data).

- H_{04}: π is GNC for u and y is GNC for u; $p = 0.0027$.
- H_{05}: u is GNC for π and u is GNC for y; $p = 0.4447$.
- H_{06}: u is GNC for π and y is GNC for π; $p = 0.0004$.

Thus we cannot reject H_{03}: π is GNC for u and π is GNC for y at conventional confidence levels, and we cannot reject H_{05}: u is GNC for π and u is GNC for y at conventional confidence levels. However, we can reject H_{04}: π is GNC for u and y is GNC for u at the 1% level, and we can reject H_{06}: u is GNC for π and y is GNC for π at the 1% level. Therefore, we conclude that the data do not support the profit squeeze theory of business cycles using the VAR model in the unemployment rate, profit rate, and log real GDP (UK data). Instead, the data suggests that log real GDP is GC for unemployment and the labour share, with no other Granger causality. The joint restrictions that imply this pattern cannot be rejected at conventional significance levels ($p = 0.7230$).

5 Concluding remarks

In this paper, the profit squeeze theory of business cycles is examined, using annual data for the USA and UK spanning the period 1960 - 2015. Using the method suggested in Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), Granger non-causality is tested between the unemployment rate and labour share, and the unemployment rate and profit rate, with and without gross domestic product as an auxiliary variable. The evidence is mixed, but on the whole it does not appear to be consistent with a strong profit squeeze mechanism during the period of study. Bi-directional Granger causality is found between the profit rate and unemployment in both the USA and UK when bivariate VARs are estimated, which is consistent with Tarassow (2010). However, the bivariate VARs in the labour share and unemployment provide less support for the profit squeeze theory, particularly in the USA.

The trivariate VARs provide very little evidence in support of the profit squeeze theory. In both the USA and the UK, direct and indirect Granger non-causality between the profit rate and unemployment rate, and direct and indirect Granger non-causality between the labour share and unemployment rate, cannot be rejected at conventional significance levels. In addition, the relevant point estimates in the trivariate VARs are usually small in magnitude, and the signs often disagree with the profit squeeze theory. This is largely inconsistent with the results in Basu et al (2013), although the latter uses investment rather than GDP and filtered data rather than data in levels.

The present paper therefore finds less support for the profit squeeze theory than a number of recent papers. There are are at least two potential reasons for this. First, the relatively unrestricted tests used in the present paper reduce biases that may affect recent papers. Second, the relatively inefficient estimates and tests used in the present paper fail to uncover effects that are correctly uncovered in recent papers. The most immediate avenue for extending the investigation is therefore to increase the efficiency of the Granger non-causality tests used; bootstrapped p-values (rather than the surplus lag method) is the most obvious possibility. Second, it may be worth repeating the investigation with quarterly data, to assess whether the observation frequency affects the inference.

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