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Do Monetary Shocks Exert Nonlinear Real Effects on UK Industrial Production?

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Production?

Abstract

This study investigates whether or not UK industrial production is characterised by a nonlinear response to monetary shocks. Our methodology is based on logistic smooth transition vector autoregression modelling where we employ monthly data for the period January 1960 to August 1999. We find evidence of small, though nonetheless significant nonlinearities. Furthermore, we find support for a range of New Keynesian arguments insofar as greater price flexibility, and therefore less real adjustment, occurs against a background of high inflation. In addition, the potency of monetary shocks can depend on the position of the UK economy in the business cycle.

JEL Codes: C3, E3, E5, E6.
Key Words: nonlinear, monetary shocks, UK output.

1. Introduction

A contentious area of macroeconomic debate is the influence of monetary policy on real output. New Keynesian macroeconomics provides models of wage and price rigidity based on optimising agents\(^1\) that can be used to justify the assertion that nominal monetary shocks lead to an asymmetric response from real output. Confirmation of asymmetries has been provided by a range of studies that include De Long and Summers (1988), Cover (1992) and Karras (1996) on the US and European economies which suggest that real output is relatively more sensitive to negative rather than positive monetary shocks. Other studies indicate that the degree of asymmetry depends on the state of the economy. For example, Rhee and Rich (1996) find that the nature of asymmetry in the US is influenced by current trend inflation. On the other hand, Beaudry and Koop (1993), Thoma (1994) and Weise (1999) find

\(^{1}\) For example, see Mankiw and Romer (1991).
that the potency of a monetary shock depends on the position of the economy on the business cycle. The objective of this paper is to investigate whether real asymmetries are present in the case of the UK economy.

There are several reasons of interest attached to our study. First, we offer a contribution to the debate over policy effectiveness with a study that is specifically geared to the UK economy. Second, our empirical approach is based on a nonlinear VAR approach. More specifically, we utilise the logistic smooth transition vector autoregression (LSTVAR) methodology. Unlike many existing studies of asymmetries, this methodology enables us to evaluate competing explanations for rigidities and nonlinearities in macroeconomic adjustment. In particular, we are able to consider the extent to which the position of the economy regarding the business cycle or the underlying rate of inflation affects the potency of monetary policy. Third, if output does exhibit nonlinearities then it is extremely difficult to forecast future economic behaviour using nonlinear models unless initial values are known exactly and parameter values remain unchanged. As suggested by Mullineux and Peng (1993), this provides a case for government stabilisation policy being based on the source of the business cycle through identification of the shocks rather than its propagation.

The paper is structured as follows. The following section reviews the relevant theoretical and empirical literature. The third section discusses the model to be estimated, the data series and econometric methodology. The fourth section reports and analyses the results. Maximum likelihood estimation suggests that nonlinearities in the response of real output to monetary shocks are present. We also find that these nonlinearities are rather smooth where the key switching variables are real output and inflation. This lends support to the notion of a convex aggregate supply curve where high rates of inflation can erode the significance of menu costs accounting for nominal
price rigidities. We also provide some generalised impulse response analysis of the real impacts of positive and negative monetary shocks of varying sizes. The final section concludes.

2. Literature

Key empirical studies that focus on the asymmetric influence of monetary shocks on real output include, *inter alia*, De Long and Summers (1988) who employ pre- and post-WWII annual US data and find that contractionary monetary shocks have a larger impact on real output than positive shocks. This is confirmed by Cover (1992) using quarterly US data for 1951Q1-87Q4 and Karras (1996) who offers a panel data study of eighteen European countries using annual data for 1953-90. There are two limitations associated with these linear studies of real output. First, they assume that the economy is always on a kink in the aggregate supply curve. Second, the extent of asymmetry might also depend on where the economy is on the business cycle [Beaudry and Koop (1993) and Weise (1999)]. In business cycle models, trend output is not dependent on short-term demand fluctuations, it is instead determined by real factors. However, deviations from trend may be attributed to short-run unanticipated demand shocks of zero mean and constant variance that are symmetric by distribution. The relative contribution of positive and negative demand shocks will depend on the shape of the aggregate supply curve. The net contribution of these shocks could be negative which means that greater demand variability could reduce trend output growth thereby yielding long-lasting non-neutral real effects [Kandil (1998)]. While the level of growth might be used as an appropriate switching variable to incorporate this channel of asymmetry, it is important that other aspects of asymmetry should be investigated. Tsiddon (1993) and Ball and Mankiw (1994) highlight the importance of an
inflationary environment in influencing the responsiveness of a firm’s price levels to monetary or nominal demand shocks. Rhee and Rich (1995) employing quarterly US data for the period 1961Q2-90Q4 find no evidence of fixed asymmetries, i.e. asymmetric effects under zero inflation, but inflation-varying asymmetries are confirmed where negative monetary shocks influence real output. Rhee (1995) examines inflation-varying asymmetries in South Korean price adjustment and finds support for the Ball and Mankiw model.\footnote{Rhee (1995) examines inflation-varying asymmetries in South Korean price adjustment and finds support for the Ball and Mankiw model.}

Inflation may constitute a switching variable that incorporates the arguments of Ball and Mankiw (1994). The role of unanticipated inflation might be incorporated through the use of changes in inflation. Output asymmetries might also be motivated by credit rationing thus monetary variables might constitute the best choice of switching variable [Thoma (1994)]. Finally, further insight into asymmetries is offered by Laxton et al. (1995) who find that G7 economic activity over the study period 1965-93 has a nonlinear effect on inflation where high levels of activity raise inflation by more than low levels of activity decrease it. The application of the LSTVAR methodology enables us to investigate these sources of asymmetry.

3. Methodology

Our investigation of asymmetries is based on a simple aggregate supply/aggregate demand model of the macroeconomy which is combined with some degree of price stickiness along with a monetary policy rule to derive an estimating form that explicitly allows for nonlinearities to pervade macroeconomic adjustment. Suppose that aggregate supply and demand are respectively specified as follows.

$$\gamma_t = \gamma_0 + \psi p_t + G(L)p_{t-1}^\text{ref} + \theta_t$$  

(1)
\[ y_t^" = y_0 - \delta (r_t - p_t) + A(L)X_{t-1} + \eta_t \]  

(2)

where \( y \) is the growth in real output, \( y_0 \) is a constant, \( p \) is the inflation rate, \( r \) is the change in the nominal interest rate, \( p^\text{oil} \) is the growth rate of the domestic real price of oil (a variable not included in the above-mentioned US-based studies), \( X \) comprises lagged values of \( y, p \) and \( r \) while \( \theta_t \) and \( \eta_t \) respectively refer to supply (technological) and demand-side shocks which are assumed to be random and independently distributed with means of zero. Under market clearing, prices adjust to equate aggregate supply and demand. Thus set (1) equal to (2) to derive the full equilibrium value for \( p^* \)

\[ p_t^* = \frac{1}{\psi - \delta} \left[ -\delta r + A(L)X_{t-1} - G(L)p^\text{oil}_{t-1} + (\eta_t - \theta_t) \right] \]  

(3)

However, prices in the economy may be subject to some degree of stickiness which inhibits the full adjustment to \( p_t^* \). Suppose that

\[ p_t = \alpha(z_t)p_{t-1} + \left(1 - \alpha(z_t)\right)p_t^* \]  

(4)

where \( \alpha(z_t) \) is a price stickiness parameter that varies according to some switching variable \( z_t \). Asymmetries in this model arise through \( z_t \) which is state-dependant.

Substituting (3) into (4) yields

\[ p_t = \frac{1 - \alpha(z_t)}{1 - \alpha(z_t)\psi} \frac{1}{\psi - \delta} \left[ -\delta r + A(L)X_{t-1} - G(L)p^\text{oil}_{t-1} + (\eta_t - \theta_t) \right] \]  

(5)

We now turn to the specification of a monetary policy rule. Following studies by Sims (1992), Strongin (1995), Clarida et al. (1998), we base our measures of monetary policy on interest rates rather than monetary aggregates. The reasoning for this is as follows. First, positive shocks to monetary aggregates have been associated with rising rather than falling interest rates [Strongin (1995)]. Second, studies have generally
found that monetary aggregates only Granger-cause output in VAR specifications that exclude interest rates [Sims (1992)]. Third, where an influence from monetary aggregates is detected, only a very small proportion of the variance in output is explained.³ Recent research on policy rules and monetary uncertainty associated with UK policy [Stuart (1996), Clarida et al. (1998) and Gerlach and Schnabel (2000)] has utilised the Taylor (1993) model where the nominal interest rate is modelled as being influenced by deviations of inflation and real growth from their target values. For these reasons it seems appropriate that \( y \) and \( p \) should play key roles in the monetary policy rule. Assume, therefore, that the change in the nominal interest rate is determined according to

\[
r_t = r_0 + \phi y_t + \pi p_t + B(L)X_{t-1} + \mu_t, \tag{6}
\]

The structural model based on (2), (5) and (6) may be represented as

\[
X_t = X_0 + C_0 X_t + C(L)X_{t-1} + J(L)p_{t-1}^{al} + D(L)\epsilon_t, \tag{7}
\]

which gives rise to the following reduced form

\[
X_t = (1 - C_0)^{-1} X_0 + (1 - C_0)^{-1} C(L)X_{t-1} + (1 - C_0)^{-1} J(L)p_{t-1}^{al} + (1 - C_0)^{-1} D(L)\epsilon_t. \tag{8}
\]

We now examine the issue of nonlinearities and the asymmetric adjustment to monetary shocks. According to Granger and Terasvirta (1993), a smooth transition autoregressive (STAR) model of order \( k \), for some variable \( e_t \) has the following specification

\[
e_t = \beta_0 + \beta_1 x_t + (\theta_0 + \theta_1 x_t) F(z_{t-\delta}) + w_t, \tag{9}
\]

Where \( x_t = (e_{t-1}, e_{t-2}, \ldots, e_{t-k}) \), \( \beta_1 = (\beta_1, \beta_2, \ldots, \beta_k) \), \( \theta_1 = (\theta_1, \theta_2, \ldots, \theta_k) \), \( w_t \sim iid(0, \sigma^2) \).

³ A further point is made by Sims (1992) who argues that if monetary authorities accommodate changes in money demand, then monetary aggregates cannot correctly reflect shifts in monetary policy.
\( F(\cdot) \) is the continuous transition function, \( z_{t-d} \) is the switching variable, and \( d \) is the delay parameter. \( F(\cdot) \) is a monotonically increasing function with \( F(-\infty) = 0 \) and \( F(\infty) = 1 \) which yields a nonlinear asymmetric adjustment. Given that our specific interest concerns asymmetric shocks, we consider the following logistic smooth transition autoregressive (LSTAR) function\(^4\)

\[
F(z_{t-d}) = \{1 + \exp[-\gamma(z_{t-d} - c)]\}^{-1}
\]

(10)

where \( \gamma \) measures the speed of transition from one regime to another and \( c \) is some threshold value for \( z \) which indicates the half-way point between the two regimes. The LSTAR model assumes that different regimes may have different dynamics and that adjustment takes place in every period but the speed of adjustment varies with the extent of the deviation from equilibrium. The transition function of LSTAR is monotonically increasing in \( z_{t-d} \) and yields asymmetric adjustment toward equilibrium in the model. Moreover, \( F(\cdot) \to 0 \) as \( z_{t-d} \to -\infty \) and \( F(\cdot) \to 1 \) as \( z_{t-d} \to +\infty \) thus \( F(\cdot) \) is bounded between 0 and 1 where \( F(\cdot) = 0.5 \) if \( z_{t-d} = c \). The smoothness of the transition curve is provided by the value of \( \gamma \). The smaller is \( \gamma \), the smoother is the transition. In the extreme, \( \gamma = 0 \) means that \( F(\cdot) \) becomes a constant and so (9) becomes a linear model. On the other hand, as \( \gamma \to \infty \) there is an ever sharper transition at \( z_{t-d} = c \) where \( F(\cdot) \) jumps from 0 to 1. In this latter case, (9) becomes the usual transition model along the lines of Tong (1983).

\(^4\) \( F(\cdot) \) can also be an even function with \( F(-\infty) = 1 \), \( F(\infty) = 1 \) being symmetric around a half-way point. This constitutes the exponential smooth transition autoregressive (ESTAR) model.
Granger and Terasvirta (1993) introduce the LSTAR model in a single-equation framework as in equation (9). We extend this model to a three equation VAR model that comprises the equations for $y$, $p$ and $r$. Thus, amending (8) we have

$$X_t = X + H(L)X_{t-1} + K(L)p_{t-1}^c + (\theta_0 + \theta_1(L)X_{t-1} + \theta_2(L)p_{t-1}^c)F(z_{t-d}) + u_t$$  \hspace{1cm} (11)

where $H = (1-C_0)^{-1}C(L)$, $K = (1-C_0)^{-1}J(L)$, $u_t = (1-C_0)^{-1}D(L)\varepsilon_t$ and $X$ is modelled as a logistic smooth transition vector autoregression (LSTVAR) model.

Our investigation of nonlinearities consists of two stages. First, we test for the linearity of the baseline VAR. To perform this, we estimate the following linear VAR

$$X_t = X + H(L)X_{t-1} + J(L)p_{t-1}^c + u_t$$  \hspace{1cm} (12)

where $(\theta_0 + \theta_1(L)X_{t-1} + \theta_2(L)p_{t-1}^c)F(z_{t-d})$ equals zero. The order of the VAR is chosen according to the BIC criterion along with Ljung-Box Q-statistics, which are used to confirm the absence of serial correlation in the residuals. We then test for the presence of nonlinearities in each equation. This linearity test is the F version of the Lagrange multiplier tests described in Granger and Terasvirta (1993) in a single-equation framework. However, we extend this procedure to a three equation VAR framework using a number of switching variables, i.e. $y$, $p$, $r$ and $\Delta p$ with the delay parameter $d$ ranging from 1 to 4. According to Terasvirta and Anderson (1992) and Terasvirta (1994), in cases where linearity is rejected for more than one value of $d$, $d$ is chosen by $d = \text{arg min} P(d)$ for $1 \leq d \leq D$, where $P(d)$ is the p-value of the linearity test.

Second, for the cases that the linearity is rejected, we estimate the LSTVAR model of equation (11). Estimation is by full information maximum likelihood where a

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5 The procedure is described in Weise (1999).
number of alternative switching variables are used, namely, \( y, p, r \) and \( \Delta p \). We can then determine the transition variable \( \gamma \) and hence the degree of asymmetry present.

### 4. Data and Results

Monthly data are employed for the period January 1960 to August 1999. This provides a sample size of 476 observations. \( y \) is measured as the first difference in the natural logarithm growth of the index of industrial production, \( p \) is the first difference in the natural logarithm of the consumer price index, and \( r \) is the change in the three month treasury bill rate, \( p^{oil} \) is the first difference in the natural logarithm of the domestic real price of oil and is assumed to be exogenous. All the data are taken from *International Financial Statistics* and the OECD *Main Economic Indicators*.

The estimation of the LSTVAR models follows Granger and Terasvirta’s recommendation (1993, p.123-124) of scaling the transition function \( F(\cdot) \) through its division by \( \hat{\sigma}(z_t) \) which is the standard deviation of the transition variable. This procedure avoids the overestimation of the adjustment parameter, \( \gamma \). Based on this scaling, the transition function is written as follows.

\[
F(z_{t-d}) = \left(1 + \exp\left(-\gamma \hat{\sigma}(z_t)(z_{t-d} - c)\right)\right)^{-1}
\]  

(13)

For each equation in the VAR, the estimates of the AR model in (12) are used as initial values for \( \beta \)'s and \( \theta \)'s. The parameter \( c \) is fixed as the sample mean of the dependant variable and the initial value for \( \gamma \) is set at 1 as suggested by Granger and Terasvirta (1993).

Table 1 reports the linearity tests in each equation of the VAR when a range of alternative switching variables are employed. These are the F versions of the Lagrange multiplier tests. When \( y \) is lagged from 1 to 4 periods and then used as a range of
alternative switching variables, the F tests suggest that the null of linearity can be rejected at the 5% significance level in the $y$ equation only. Here we find that nonlinearities are not present in $p$ and $r$. A similar story prevails when the same range of lags in $p$ are used as alternative switching variables. However, this time linearity in $y$ is only rejected throughout at the 10% significance level. More extensive evidence of nonlinearity occurs in $y$, $p$ and $r$ when lagged values of $r$ are used as alternative switching variables. On these occasions we find that the null of linearity is rejected at the 5% significance level in nine out of twelve cases. Finally, when lagged values for $\Delta p$ are used as alternative switching variables we find that linearity is accepted in all cases even at very generous levels of significance.

These results have important implications for the source of asymmetry. The confirmation of $y$ as a switching variable in the $y$ equation suggests that positive and negative monetary shocks exert asymmetric effects where the size of these effects depends on the position of the economy in the business cycle. This is consistent with the existence of a convex AS curve. The use of $p$ as a switching variable in the $y$ equation supports Ball, Mankiw and Romer (1988) and Ball and Mankiw (1993) who argue that higher rates of inflation diminish the significance of menu costs as a source of real rigidities. The use of $r$ as a switching variable might support the notion that asymmetries are, to some extent, motivated by credit rationing. These results may be compared with Weise (1999) who finds nonlinearities in $y$ exist in the US when lags in $y$, $p$ and $\Delta p$ are used as alternative switching variables.

The second part of the empirical investigation is to estimate the specified LSTVAR model by using full-information maximum likelihood techniques. By doing this, we are in a position to estimate the smoothness parameter $\gamma$. We also conduct a
test of linearity on the system as a whole by using a log-likelihood ratio test based on
the use of \( y, p \) and \( r \) as alternative switching variables\(^6\), which is to test for the null
hypothesis that all the coefficients in \( \theta_0 + \theta_1(L)X_{t-1} + \theta_2(L)p_{t-3}^{out} \) are equal to zero.
The LR statistic is distributed as \( \chi^2(6) \) on the null. Table 2 reports that system-wide
linearity is rejected at the 10% level or better when \( y_{t-3}, p_{t-2}, p_{t-3}, r_{t-1} \) and \( r_{t-3} \) are
used as alternative switching variables. In the remaining cases, either linearity is
accepted or convergence was not achieved during estimation. We find that \( \gamma > 0 \)
where nonlinearities are confirmed with values ranging from 0.340 to 10.834. In
contrast, Weise (1999) finds that \( \gamma \) ranges in value from 0 to 67.75 which suggests
greater extremes in the smoothness of adjustment. Given that \( \gamma \) can range between 0
and \( \infty \), both of these sets of results point towards nonlinearities that are fairly small.
One possible explanation for the very small degrees of nonlinearity might be that in the
aggregate these are averaged out and that nonlinearities are more likely to be observed
in disaggregated data according to industry [Mills (1995)].

Having confirmed that nonlinearities are present in the output equation, we can
now look more specifically at how output responds to positive and negative monetary
shocks. For this purpose, we can compute a generalised impulse response function, as
proposed by Koop et al (1996), for specific shocks applied to nonlinear models.
Consider the following formulation.

\[
GL_Y(n, v, \omega_{t-1}) = E[Y_{t+n}|v, \omega_{t-1}] - E[Y_{t+n}|\omega_{t-1}]
\]

(14)

where \( GL_Y \) denotes the generalised impulse response function of some variable \( Y \), \( n \) is
the forecast horizon \( (n = 1, 2, ...N) \), \( v_t \) is the shock generating the response, \( \omega_{t-1} \) is the

\(^6\) We do not continue with the use of \( \Delta p \) as a switching variable because rejection of linearity in at
historical or initial values of the variables in the model and $E[.]$ is the expectations operator. This procedure includes several steps. First, for given initial values of the variables, the random shocks for periods 0 to $q$ are drawn from the residuals of the estimated LSTVAR model (here a bootstrap method is used), and then fed into the model to derive a simulated data series. This is a forecast of the variables conditional on initial values and a particular sequence of shocks. Second, the monetary shocks in period 0 are fixed at some value, for example one or two standard deviation of the monetary residuals, and the random shocks to other variables in all the periods and to the monetary variable in periods 1 to $q$ are the same as above. The shocks are then fed into the model and a forecast is produced. Finally, the difference of the values between the second step and the first step is the impulse response of a particular sequence of shocks and initial values. This procedure is repeated 1,000 times and averaged to produce the impulse response function conditional only on initial values.

Figure 1 shows the implied dynamic responses to shocks applied to the estimated LSTVAR model with $y_{t-3}$ as a switching variable. We impose four different monetary shocks to investigate its impact and magnitude on industrial production, i.e. $v_t = \pm \hat{\sigma}$ and $v_t = \pm 2\hat{\sigma}$, with $\hat{\sigma}$ being the standard deviation from the linear VAR model expressed in equation (12). Let us denote n1 and n2 (p1 and p2) as shocks measured according to negative (positive) one and two times $\hat{\sigma}$. The response analysis is based on these monetary shocks being applied two dates representing expansion (1985.05) and recession (1991:03). Earlier it was argued that the small values for $\gamma$ suggest that asymmetries are slight. To make the asymmetric effects more easily identifiable, we plot the difference of the generalised impulse response between n1 and n2.
p1 as well as the difference between n2 and p2. Figure 1 reveals general evidence that during a recession or expansion, a negative monetary shock reduces UK industrial production by more than an equivalent positive shock raises industrial production. In all cases the real effects eventually diminish towards zero.

5. Summary and Conclusion

Using the logistic smooth transition vector autoregression methodology we are able to confirm the presence of small but nonetheless significant nonlinearities in the adjustment of UK industrial production to monetary shocks. We can also identify support for various strands of the New Keynesian literature. The use of real output growth as a switching variable points to negative monetary shocks having a more potent effect on real output than equivalent positive shocks. Furthermore, the extent of asymmetry can depend on the position of the UK economy in the business cycle. The use of inflation as a switching variable points to the role of inflation in eroding the effectiveness of menu costs in preventing nominal price adjustment. This suggests a limited potency of monetary shocks during periods of high inflation. The use of interest rate changes as a switching variable might point towards the role of credit rationing in asymmetries. It is possible that the presence of small nonlinearities at the aggregated level is masking more dramatic experiences at the disaggregated level. Given that our evidence suggests that nonlinearities are probably only slight, avenues for future research might include investigations at a more disaggregated level where specific industries may be considered.
<table>
<thead>
<tr>
<th>( z )</th>
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<th>( r )</th>
<th>( z )</th>
<th>( y )</th>
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Notes for Table 1. The column headed ’\( z \)’ refers to the switching variable, the columns headed ’\( y \)’, ’\( p \)’ and ’\( r \)’ refer to the estimates associated with the particular equations in the LSTVAR model. Figures in parentheses are the p-values for the F test.

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</tbody>
</table>

Notes for Table 2. These results are for the output equation. The row beginning ’\( z \)’ refers to the alternative switching variables. LR is a likelihood ratio test of system-wide linearity distributed as \( \chi^2(6) \) on the null of linearity. The critical values for the 5% and 10% significant levels are 12.6 and 10.6 respectively. \( \gamma \) is the estimated smoothness parameter derived from \( F(z_{t-d}) = [1 + \exp((-\gamma / \sigma(z)) (z_{t-d} - c))]^{-1} \).
Figure 1. Generalised Impulse-Response Analysis of Positive and Negative Monetary Shocks on UK Industrial Production

a. Monetary shock at 1991:03

![Graph for monetary shock at 1991:03]

b. Monetary shock at 1985:05

![Graph for monetary shock at 1985:05]

Notes for Figure 1. Negative (positive) monetary shocks defined as n1 and n2 (p1 and p2) correspond to positive (negative) interest rate movements. The calculation of n1-p1 and n2-p2 are based on absolute values for n1, n2, p1 and p2.
References


