Technology Shocks and UK Business Cycles

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Abstract

After a neutral technology shock, hours worked decline in a persistent manner in the UK. This response is robust to a variety of considerations in the recent literature: measures of labour input, level versus differenced hours in the VAR, small and large VARS, long- versus medium-run identification, and neutral versus investment-specific technology shocks. The UK economy, therefore, offers a unique perspective on the response of hours to technology shocks. The large negative correlation between labour productivity and hours is the source of this response. Models with nominal price stickiness, low substitutability between domestic and foreign consumption, and investment-specific shocks appear to be most plausible in interpreting the short-run effects of technology shocks. Quantitatively, however, technology shocks account for under 20% of the business cycle variation in hours and under 30% of business cycle variation in output. These findings suggest that technology shocks may play only a limited role in driving UK business cycles.

JEL classification: E32, E24

Key words: Technology shocks, business cycles

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1 Introduction

A central feature of economic fluctuations is the positive co-movement of economic activity and labour input measures. Real business cycle (RBC) theory, developed following the contribution of Kydland and Prescott (1982), emphasizes shocks to technology as drivers of economic fluctuations, and predicts an increase in output and hours-worked after positive technology shocks. Galí (1999), however, has shown that positive technology shocks, identified as permanent shocks to labour productivity via long-run restrictions in a structural vector-autoregression (SVAR), lead to a decline in hours worked in the post World War II US data. Similarly, Basu et al. (2005), using an augmented growth accounting approach to identify technology shocks, find that hours decline after technology improvements.[1] These findings suggest that technology shocks are not a major source of economic fluctuations and, consequently, do not support the RBC view of business cycles. Moreover, models with nominal price stickiness generate a decline in hours if monetary policy does not fully accommodate the technology shock, and therefore, are consistent with the empirical evidence.

A large body of recent literature has reinforced or debated these conclusions, and their implications for evaluating business cycle theories, from a variety of standpoints.[2] In particular, issues include whether identified shocks represent variations in technology (Francis and Ramey (2004)); the treatment of hours in the SVAR (Christiano et al. (2003)); small-sample biases and weakness of long-run restrictions in identifying technology shocks when non-technology shocks can also have permanent effects on labour productivity (Faust and Leeper (1997), Uhlig (2004), Erceg et al. (2005), Christiano et al. (2005)); low-frequency correlation between hours and productivity (Fernald (2005)); and the role of investment-specific versus neutral technology shocks (Fisher (2005)).

In this paper we examine the response of hours to identified technology shocks in the UK and assess the plausibility of alternative models in accounting for that response. We then quantify the importance of technology shocks in driving UK business cycles. In doing so, we pay close attention to the important considerations mentioned above. Our analysis can, therefore, provide a useful perspective on the generality of the issues raised in the recent US literature.

We consider two measures of output and labour input (hours and employment), namely, whole

[1] Shea (1998) identifies shocks to R&D and patent applications as more direct measures of stochastic variations in technology. He finds that technology shocks increase short-run labour input and reduce it in the long run.

[2] See Galí and Rabanal (2004) for a detailed discussion and overview of the literature.

economy and private sector measures. The sample period is 1971 Q1 - 2004 Q4 for whole economy measures, and 1987 Q1 - 2004 Q4 for private sector measures. In addition, we use data on other macroeconomic variables described in the later sections.

To identify technology shocks, we consider two types of restrictions. First, the long-run restriction requiring that unit root in labour productivity is exclusively driven by technology shocks. Following Galí (1999), this restriction is extensively used in the literature. Second, the medium-run restriction, proposed by Uhlig (2004), which identifies the most persistent shock to labour productivity over a three to ten year horizon without imposing a unit root. This identification scheme is motivated by the concern that shocks other than technology (eg. capital income tax) can also have a permanent effect on labour productivity invalidating the identifying assumption under long-run restrictions. Using simulated data from dynamic general equilibrium model, Uhlig (2004) shows that medium-run restrictions are more robust relative to long-run restrictions in identifying technology shocks. Another concern with long-run restrictions, as Faust and Leeper (1997) show, is that the difference between a very persistent and a unit root process in finite data may not be pronounced leading to less reliable identification.

We begin by considering a bivariate-SVAR framework in labour productivity growth and total hours (in first-differences) as in Galí (1999). We find that after a positive technology shock, hours decline in a persistent manner in the UK. The response of hours does not change if hours are specified in levels in the VAR. The finding that hours decline under *both* difference- and level-specifications for the UK is in sharp contrast to the findings of Christiano et al. (2003) for the US data. They find that in the level-specification, hours rise after a positive technology shock, consistent with the prediction of an RBC model. Relative to the debate in the US literature, therefore, the level- versus difference-specification of hours appears to be unimportant for the UK.

Following the recommendations of Erceg et al. (2005) and Christiano et al. (2005), we consider larger VAR systems to minimize the potential small-sample biases associated with long-run identification. We also use the alternative medium-run restriction, without imposing a unit root in labour productivity. The response of hours in these larger VAR systems and under both identifications schemes is the same, that is, they decline after a positive technology shock.

What drives the hours response in the UK? To answer this question, we present an analytical discussion similar to that in Fernald (2005), based on the Shapiro and Watson (1988) methodology to impose long-run restrictions. In the level-specification, the response of hours to technology shocks is driven largely by the negative covariances of labour productivity growth with current and lagged hours in the data. By contrast, Fernald (2005) finds that both covariances in the US data are positive, leading to a positive response of hours to technology shocks when hours are in levels. Similarly, in the difference-specification, the negative covariances that drive the response of hours are between labour productivity growth, and the current and lagged growth rate of hours. The large negative correlation between labour productivity and hours (-0.40 for HP filtered data and -0.27 for growth rates) are consistent with these negative covariances.

Next, using the methodology of Fisher (2005), we identify both neutral (N) and investment-specific (I) technology shocks , and examine their effects on hours, output, investment, and productivity. For neutral shocks, the effects are the same as when these shocks alone are identified. By contrast, both hours and output rise in response to I-shocks. This positive co-movement is consistent with the contemporaneous correlations in the data, and also consistent with the theoretical prediction of a model with such shocks. Investment also surges in response to this shock, whereas it is muted in response to an N-shock. Productivity, however, declines in a persistent manner whereas the model predicts that it recovers after an initial decline. We find the responses to I-shocks to be sensitive across small and large VARs, and also to a mean break in the nominal investment-output ratio. Interestingly, as it turns out, both the recommendations of Erceg et al. (2005) and Christiano et al. (2005) to include nominal consumption-to-output and nominal investment-to-output ratios in the VARs to eliminate small-sample biases, and the recommendation of Fernald (2005) to allow for breaks appear to be important in the context of examining the implications of estimated I-shocks for the UK.

Based on the pattern of impulse responses, our findings suggest that three classes of models may be most plausible in interpreting the short-run effects of technology shocks in the UK. First, the models with nominal price stickiness as pointed out in Galí (1999). Second, the augmented RBC model which generate a decline in labour input in response to technology shocks via strong wealth effects. Within this class, Francis and Ramey (2004) consider a flexible price model with real rigidities such as habit-formation and capital adjustment costs to rationalize the decline in hours. Given the persistent decline in hours worked in the UK, it is, however, difficult to gauge whether real frictions of this sort are particularly strong in the UK economy. Groth (2005), for example, finds that estimated capital adjustment costs in the UK are broadly similar to the estimates for the US. An alternative possibility in this class, as suggested by Collard and Dellas (2004), is an open-economy RBC model with low elasticity of substitution between domestic and foreign consumption. Empirical evidence in Hooper et al. (2005) indicates that this elasticity for the UK is indeed small. The Collard and Dellas (2004) model, therefore, appears to be relevant in the UK context. Third, models that emphasize investment-specific relative to neutral technology shocks, as in Greenwood et al. (2000) and Fisher (2005), to interpret the co-movement of hours and output, and the response of investment.

We conduct a quantitative analysis to determine the role of technology shocks in driving UK business cycles. In terms of forecast error variance decompositions, we find that the I-shocks contribute more to the forecast error variance of hours than the N-shocks over horizons of four to twenty quarters. N-shocks contribute relatively more to the forecast error variance of output over the same horizons. The contributions of such shocks over these horizons, however, remain less than 30%. Comparing it with the results in Fisher (2005) for the US, we find that in quantitative terms the percent contributions of both shocks are smaller at these horizons.

Turning to business cycle effects, the relative cyclical variances of hours and output accounted for by N-shocks in the UK are small and similar in magnitude as those in the US data, as in Galí (1999) and Christiano et al. (2003). The cyclical variances accounted for by I-shocks are, however, substantially smaller compared to those in Fisher (2005). Quantitatively, technology shocks account for under 20% of the business cycle variation in hours and under 30% of business cycle variation in output. These findings suggest that technology shocks may play only a limited role in driving UK business cycles.

Finally, we conduct several robustness checks and provide corroborative evidence to establish that the permanent shocks to labour productivity in the UK data, identified as technology shocks, are indeed capturing variations in technology.

The paper is organized as follows. In Section 2 we describe the data, some key correlations, and the identification methodology. Section 3 presents the results and plausibility of alternative models. In Section 4 we examine the business cycle implications. Section 5 presents robustness analysis. Section 6 concludes.

2 Data and identification

In this section we describe the UK data and some key business cycle correlations. We then discuss the methodology for identifying technology shocks.

2.1 Data

We consider two measures of output and labour input, namely, whole economy and private sector measures. The variables are in logs and the data period is 1971 Q1 - 2004 Q4 for whole economy measures, and 1987 Q1 - 2004 Q4 for private sector measures.[3] Figure 1 displays the whole economy labour input measures (hours and employment measures). Figure 2 displays labour productivity growth, hours per capita (16-64 years), inflation, real interest rate, nominal investment-to-output ratio, and nominal consumption-to-output ratio, variables we use in our empirical analysis.

2.2 Contemporaneous correlations

Table 1 documents key business cycle contemporaneous correlations of cyclical and growth rates in output, two measures of labour input (employment and total hours), and labour productivity (defined as either output per worker or output per hour) for both whole economy and private sector data.[4] Several notable aspects emerge from Table 1. For the HP filtered data, the output-hours correlation is large and positive, indicating the strong positive co-movement which typically characterizes business cycles. Similarly, the output-employment correlation is also large and positive. In terms of growth rates, the correlation is somewhat higher for the private sector measures. The output-labour productivity correlations are positive for the HP filtered data implying procyclical labour productivity. For the private sector measure, however, the correlation between cyclical output (using the HP filter) and labour productivity per hour is negative.

Most notably, the correlation between labour productivity and hours or employment (in bold) is large and *negative*. The correlations for whole economy measure range from -0.09 to -0.40. The correlations for private sector measure are even lower, ranging from -0.30 to -0.60. By way

[3]The private sector is defined as whole economy minus public administration, minus health and education sectors.

[4]Early paper by Blackburn and Ravn (1992) document the properties of UK business cycles (over 1956-1990) and compared it with the US. They note that cyclical variations in labour at the intensive margin (hours per worker) and the extensive margin (employment) are similar, but less pronounced relative to the US. In the US, roughly three-quarters of cyclical variation in total hours is accounted for by variations in employment.

of contrast, in the US data the correlation between business sector productivity and hours over the period 1971 Q1 to 2004 Q4 is zero.[5] As stressed by Christiano and Eichenbaum (1992), the standard technology shock driven RBC model implies a large and positive correlation between labour productivity and hours. That model, by overstating the observed correlations, therefore, fails to account for this feature of the US data. They suggest augmenting the standard RBC model to include demand shocks (in particular government spending shocks) can help lower the implied theoretical correlations and thereby help improve the prediction of the model along this dimension. Similarly, in the case of UK, even larger negative unconditional correlations between labour productivity and hours relative to the US, in both the whole economy and the private sector data, clearly pose a strong challenge to the technology shock driven view of cyclical fluctuations. We discuss this aspect further in Section 4.

2.3 Identification of technology shocks

We consider two methodologies for identifying technology shocks: long-run and medium-run restrictions used in structural VAR (SVAR) literature. We provide a brief discussion of both methodologies.[6]

2.3.1 Long-run identification

Consider a moving average representation of a structural model

$$y_t = \Phi(L)\epsilon_t \tag{2.1}$$

where $y_t = [\Delta lp_t \;\; h_t \;\; z_t]'$ and $\epsilon_t = [\epsilon_t^T \;\; \epsilon_t]'$. Δlp_t is labour productivity growth, h_t is hours (either differenced, in levels, or quadratic detrended), z_t is an $kX1$ vector of additional variables. ϵ_t^T and ϵ_t are technology and non-technology shocks, respectively. The dimension of ϵ_t is $(k+1)X1$. The variance-covariance matrix $E\epsilon_t\epsilon_t' = I$ (normalized to an identity matrix). $\Phi(L)$ is a matrix polynomial in the lag operator L.

[5] Christiano and Eichenbaum (1992) document a correlation of -0.20 for U.S. data for the period 1955 Q4 to 1983 Q4. Similarly, Uhlig (2004) reports employment-productivity correlations close to zero (0.04 for HP filtered data and -0.05 for growth rates) in the US historical data of Francis and Ramey (2002).

[6] The methodology of Shapiro and Watson (1988) provides an alternative way to implement long-run restrictions. Detailed expositions are given, for example, in Blanchard and Quah (1989), King et al. (1991), and Galí (1999).

Consider the reduced form vector-autoregression (VAR) representation of the structural model

$$y_t = A(L)y_{t-1} + u_t, \quad E_t u_t u_t' = \Sigma \tag{2.2}$$

$A(L)$ is a matrix lag polynomial, $\Delta = 1-L$, and Σ is the variance-covariance matrix of the residuals. The residuals are linearly related to the structural (or fundamental) shocks as

$$u_t = G\epsilon_t, \quad GG' = \Sigma \tag{2.3}$$

Using (2.3), the long-run effects in (2.2) are given as

$$y_t = [I - A(1)]^{-1}G\epsilon_t = \left(\sum_{j=0}^{\infty}\Phi_j G\right)\epsilon_t = \Phi(1)G\epsilon_t \tag{2.4}$$

We estimate the elements of matrix G to compute the dynamic responses of variables in vector y_t. In the bi-variate VAR case, for example, the restriction $GG' = \Sigma$ gives three equations in four unknown elements of G. The fourth equation comes from the restriction that non-technology shock has no long-run effect on productivity, implies that the $(1,2)$ element of $\Phi(1)G$ matrix is zero. We estimate (2.2) and compute $A(1)$. We compute the lower triangular Choleski matrix, C, such that $CC' = \Phi(1)\Sigma\Phi(1)'$. Since $\Phi(1)G$ is a factor of $\Phi(1)^{-1}\Sigma\Phi(1)^{-1'}$, we can use the equation $G = \Phi(1)^{-1}C$. With estimates of the elements in G in hand, we can compute the impulse responses and the decompositions labour productivity and hours due to the two shocks.

2.3.2 Medium-run identification

The long-run identification described above is extensively used in the literature. It obtains a shock that explains the variance of the forecast error revision in productivity in the long-run (theoretically this is infinite horizon). In finite samples, however, the long-run identification of shocks may be less reliable as discussed in Faust and Leeper (1997). One difficulty is that in finite data the difference between a very persistent and a unit root process may not be pronounced.[7] Alternatively, as argued by Uhlig (2004), shocks other than technology (eg. capital income taxation, labour supply) may have a persistent effect on labour productivity and technology shocks alone cannot explain the forecast error revision variance of labour productivity in any horizon.

[7] Long run identification implies very weak restrictions on $\Phi(L)$ and transfers the uncertainty of a VAR estimate of $\Phi(1)$ in all horizons via equation (2.4). Finite restrictions in effect alleviate this problem by imposing some more structure on $\Phi(L)$, for e.g. that the effect of shock i is zero at horizon k.

Uhlig (2004) proposes medium run restrictions as a means of identifying most persistent shock to labour productivity over a three to ten year horizon (the medium run) without imposing a unit root (as in Galí (1999)). Using simulated data, he demonstrates that medium run identification is more robust relative to long run identification even in the case where there are multiple shocks. For standard parameterizations of his model, the medium run restriction better identifies the technology shock which contributes most to the productivity forecast error revision variance over the medium run. In this manner it overcomes the critique that long run identification may be fragile in small samples.[8] We, therefore, consider medium run identification in addition to long run identification to identify technology shocks. Practical implementation of identification scheme is similar to (2.4) with the only difference that

$$y_t = \left(\sum_{j=0}^{k} \Phi_j G \right) \epsilon_t \tag{2.5}$$

when labour productivity is in first-difference or

$$y_t = \Phi_k G \epsilon_t \tag{2.6}$$

when we identify persistent but not permanent shocks to labour productivity, and where $k = \{3, 4, ..., 10\}$ years depending upon the assumed duration of the medium run.

3 Results

Using the two identification schemes, we present responses of variables to estimated technology and non-technology shocks in the UK. We focus, in particular, on the response of hours in light of several important considerations discussed and debated in the recent literature.

3.1 Level versus first-difference hours

Galí (1999), using the long-run restriction with hours in first differences, finds that hours fall after a positive technology shock. This estimated response in the US data is opposite to the prediction of a standard RBC model that hours should rise after a positive technology shock. Christiano et al. (2003)), however, have argued that hours per capita are stationary and should enter the VAR in

[8] Francis, Owyang and Theodorou (2005) propose a similar identification where the unit root in labour productivity is not imposed. In their procedure, the finite horizon corresponds to one which has a maximum forecast error variance for productivity.

levels and not first-differences. They find that hours rise after a technology shock when hours per capita enter the VAR in levels.[9]

3.1.1 Unit root and stationarity tests

We conduct unit root and stationarity tests and examine the time series properties of the data used in the econometric analysis. Table 2 presents evidence on the presence of a unit root in labour productivity based on a ADF and KPSS tests, and results from the stationarity tests for hours per capita, total hours, and employment.[10]

The ADF tests for labour productivity indicate that the null of a unit root cannot be rejected in the level of the series, but reject the same null when applied to the first differences at the 1% level or above (not shown in Table 2). On the other hand the results for the various labour input measures give a mixed picture. In the case of whole economy per capita hours, the ADF test cannot reject the null of a unit root at the 10% level. The KPSS test rejects the null of stationarity at the 10% level. For the private sector measure of hours per capita, however, both tests point to stationarity of the level series, giving a consistent answer concerning the stationarity of the series. For total hours, the ADF test rejects the null of a unit root and the KPSS test does not reject the null of stationarity, although in the latter case the test statistic is very close to the 10% critical value.

We choose total hours as our preferred measure of labour input since both ADF and KPSS tests indicate stationarity (Table 1), whereas for per capita hours the results are inconclusive.[11] However, we consider VAR specifications where hours enter either in differences (implying non-stationarity) or in levels (implying stationarity) in light of the important debate in the literature summarized above. All the results in this section are qualitatively the same when 'per capita hours' are used instead.

[9] See Galí (2005), for a detailed discussion of non-stationarity of hours. Whelan (2004) finds that the stochastic trend specification considered in Galí (1999) is robust to a variety of data transformations, other issues concerning VAR specifications.

[10] While low power of unit root tests is well known, long-run identification of permanent technology shocks hinges critically on the presence of a unit root in labour productivity.

[11] Labour productivity is invariant to the choice of total or per capita hours. In the literature it is common to use per capita hours since this measure relates directly to the theoretical hours worked variable in an RBC model.

3.1.2 Technology shocks

The VAR contains labour productivity growth Δlp_t and first difference of 'total hours' (referred as 'hours') with two lags.[12] Figure 3 displays the estimated responses to a positive technology shock for the whole-economy data, along with bootstrapped error bands.[13] Hours worked fall on impact. This response is statistically significant and very persistent. Figure 4 shows the impulse responses for the private sector data. The response of hours is similar to that for the whole-economy data; hours fall in a persistent manner.

Turning to the estimated response of output, in both whole-economy and private-sector data, the response is not statistically significant. Point estimates, however, indicate that output decreases in a persistent manner. In the whole-economy data the persistent decline occurs after an initial increase which lasts for two quarters. Galí (2005) documents a similar persistent decline in output, although statistically significant, using annual UK data for the period 1970-2003.[14] The unconditional contemporaneous correlations between labour productivity growth and hours growth in annual and private sector data sheds light on the similarity of output responses in Figure 4 and those in Galí (2005). The correlations are approximately the same, -0.56 in the annual data and -0.59 in the private-sector data. Although the persistent negative output response is puzzling, we find that it is not robust as discussed below.

Figures 5 and 6 present the responses when hours enter the VAR in level (with four lags) for the whole-economy and private-sector data, respectively. We find that hours fall persistently for approximately ten quarters. The drop is statistically significant. This finding for the UK data is in sharp contrast to what one obtains for the US data. We conclude that in the UK data the estimated responses of hours to technology shock are similar when hours enter the VAR in differences (as in Galí (1999)) or in levels (as in Christiano et al. (2003)). In *both* cases hours fall after a technology shock. Relative to the debate in the U.S. literature, therefore, the level- versus difference-specification of hours appears to be unimportant for the UK. Note that when hours enter the VAR in levels, the estimated response of output is positive and statistically significant.

[12] We used the standard Akaike Information Criterion and the Schwarz Bayesian Criterion to test for lag lengths. We have decided to implement a lag length equal to $\max\{AIC, SC\}$.

[13] The bootstrapped standard error bands are computed from a 1000 draws from the distribution of estimated residuals with replacement. For each draw we estimate the model given pre-sample values from the data and recover the impulse responses. The standard error bands are the 95th and 5th quantiles from the distribution of impulse responses.

[14] That data are constructed by the OECD and part of the their Labour Force Statistics.

Interestingly, the level specification for hours in the VAR reverses the sign of the output response.

Recently, Fernald (2005) has showed that once trend breaks in US productivity (which occurred in early 1970s, when productivity declined, and after mid-1990s, when productivity accelerated) are accounted for then hours decline after a technology shock even when they enter the VAR in levels.[15] When these, statistically and economically plausible, trend breaks are not accounted for then hours rise as in Christiano et al. (2003). Since in the UK both the level and difference specification of hours yield the same response of hours to technology shocks, the potential low frequency correlation between productivity and hours appear to be less important over the sample period. Moreover, we do not detect a break in UK labour productivity in the sample. We interpret our results to be consistent with Fernald (2005) as he finds that in sub-samples (periods with no productivity breaks), hours (in levels) fall after a technology shock in the US data.

3.1.3 Non-technology shocks

Figures 3 to 6 also display the estimated responses to a non-technology shock. While the effect on productivity is temporary (due to the identification assumption), both hours and output rise in a persistent manner. The non-technology shock generates a positive comovement between productivity and hours similar to that found in Galí (1999). Table 4A reports the conditional correlations between labour productivity and the different labour input measures based on the bi-variate VAR specification. Notice that the conditional correlations between non-technology shocks and the labour input measures are positive. This positive sign implies that for the UK, an augmented RBC model with multiple shocks (eg. technology and government spending shocks) may not help lower the implied correlation between productivity and hours to match the data as suggested by Christiano and Eichenbaum (1992).

3.2 Larger VAR systems and medium-run identification

In this section we focus on technology shocks identified from larger VAR systems with additional macroeconomic variables.[16] The findings of Erceg et al. (2005) based on simulated data suggest

[15] Gambetti (2005) develops a time-varying coefficients Bayesian vector autoregression methodology and finds that under both level and first-difference specifications, hours fall in response to a positive technology shock in the U.S. data. This finding is consistent with those of Fernald (2005), and appears to be an alternative way of accounting for the effects of low frequency correlation between labour productivity growth and hours in the U.S..

[16] We identify only the technology shock and not other sources of fluctuations, for example, monetary shocks, as in Altig et al. (2004).

that a larger VAR with nominal consumption-output and nominal investment-output ratios helps minimize the small-sample biases in hours response RBC model documented in Chari et al. (2005). Christiano et al. (2005) also recommend including these ratios to eliminate small sample bias. More generally, Erceg et al. (2005) show that such low-ordered VARs (with four lags) provide a close approximation to the true data generating processes that are based on different parameterizations of the DSGE models.

We examine the responses from two larger VAR systems. First, a four-variable VAR system that includes logs of labour productivity, hours, nominal consumption-output ratio, and nominal investment-output ratio.[17] We specify hours in levels and do not impose a unit root on labour productivity. We use the medium-run restriction with a 40-quarter horizon to identify technology shocks.[18] As discussed in Section 2, medium-run restriction addresses the criticisms of using long-run restrictions. Figure 7 shows the responses to technology shocks for this VAR system. Second, a six-variable VAR which, in addition to the above variables, includes inflation and real interest rates. Inflation is defined as the annualized rate computed from the GDP deflator, and the real interest rate (ex-post) computed as the difference between the repo rate and the above measure of inflation. Both the real interest rate and the inflation rate enter with a quadratic trend removed. Figure 8 shows the responses to technology shocks for this six-variable VAR.[19]

In both VAR systems, hours fall for three to five quarters after a positive technology shock. This response is statistically significant and consistent with response from the bi-variate VAR discussed above.[20] Output and consumption rise and the responses are statistically significant. Investment, however, does not appear to respond much to the positive technology shock.

[17]These are ratios of nominal personal consumption expenditures to nominal GDP and nominal business investment to nominal GDP, i.e. the consumption and investment shares of output. In addition we remove a linear trend from the consumption share.

[18]Results from alternative definitions of 'medium run' ranging between 8 and 20 quarters are very similar. We also considered the difference specification and sensitivity to lags in the VAR but do not report due to space limitations. The responses of labour input measures are qualitatively similar. These results are available upon request.

[19]Francis, Owyang and Theodorou (2005) extend the analysis of Galí et al. (2003), and examine the endogenous response of monetary policy in a G-7 context. They consider the employment index as the labour input measure for the UK in their analysis.

[20]We also considered specifications with different treatment of the low frequency components of these variables, e.g. levels or difference hours specification, medium or long run restrictions, deterministic trends etc. In all the experiments, the labour input response to the technology shock is the same, it declines in response to a positive technology shock. More discussion on the low frequency considerations follows in section 5.

3.3 What drives the hours response in the UK?

The previous sections established a robust finding that hours in the UK decline after a technology shock. In this section we follow a very useful analytical discussion in Fernald (2005) to explain the response of hours, based on the Shapiro and Watson (1988) methodology to impose long-run restrictions. This methodology is an equivalent way of identifying technology shocks as compared to the approach discussed in Section 2.3.1. It involves estimating two regressions. Since our objective is to provide an intuitive discussion, we consider a simplified form (without lags) of the two regressions as in Fernald (2005).

3.3.1 Stationary hours

When hours are treated as stationary or $I(0)$, the regressions are

$$\Delta lp_t = \alpha \Delta n_t + \epsilon_t^T \tag{3.1}$$

and

$$n_t = \beta \epsilon_t^T + \epsilon_t^{NT} \tag{3.2}$$

In (3.1), the contemporaneous effects of ϵ_t^{NT} shocks influence Δlp_t through n_t. To impose the restriction that ϵ_t^{NT} shocks do not affect productivity in the long run, hours are specified in differences (see, Shapiro and Watson (1988) for details). Since ϵ_t^T might affect the current hours growth, (3.1) is estimated with instrument variable method, using n_{t-1} as an instrument. The residuals from (3.1), $\hat{\epsilon_t}^T$, are the estimated technology shocks. These shock enter (3.2) in order to achieve orthogonality between the technology and non-technology shocks. Using $\hat{\epsilon_t}^T$, we can estimate (3.2) by OLS. The estimate

$$\hat{\alpha} = \frac{n'_{t-1}\Delta lp_t}{n'_{t-1}\Delta n_t} \tag{3.3}$$

is the estimated impact of non-technology shock on productivity. The estimate

$$\hat{\beta} = \frac{\hat{\epsilon_t}^{T'} n_t}{\hat{\epsilon_t}^{T'} \hat{\epsilon_t}^T} \tag{3.4}$$

is the estimated impact of technology shock on hours, where $\hat{\epsilon}_t^T = \Delta lp_t - \hat{\alpha}\Delta n_t$. The $sign(\hat{\beta}) = sign(\hat{\epsilon_t}^{T'} n_t)$, since the denominator in (3.4) is positive. Re-writing the covariance term $n'_t \hat{\epsilon_t}^T$ as

$$\hat{\epsilon_t}^{T'} n_t = (\Delta lp_t - \hat{\alpha}\Delta n_t)' n_t = \underbrace{\Delta lp_t' n_t}_{-} - \underbrace{\left(\frac{n'_{t-1}\Delta lp_t}{n'_{t-1}\Delta n_{t-1}}\right)\Delta n_t' n_t}_{+} < 0 \tag{3.5}$$

In the UK data, $n_t'\Delta n_t$ is positive. Moreover, $\Delta lp_t' n_{t-1}$ and $\Delta n_t' n_{t-1}$ are both negative, consistent with the positive impact of non-technology shock on productivity discussed in Section 3.1. The sign of these covariances implies that the second term on the right hand side of (3.5) is positive. The first covariance term, $n_t'\Delta lp_t$, is negative in the data. The estimated impact of a positive technology shock on hours is, therefore, negative. By contrast, Fernald (2005) finds that both covariances terms, $n_t'\Delta lp_t$ and $n_{t-1}'\Delta lp_t$ are positive in the U.S. data when the low-frequency correlation between productivity growth and hours is not taken into account, leading to a positive response of hours.

3.3.2 Unit root in hours

When hours are treated as having a unit root or $I(1)$, hours enter (3.1) in double differences. That is,

$$\Delta lp_t = \alpha \Delta^2 n_t + \epsilon_t^T \tag{3.6}$$

Using Δn_{t-1} as instrument, we can estimate (3.6). The equation corresponding to (3.5) is

$$\hat{\epsilon}_t^{T'} \Delta n_t = (\Delta lp_t - \hat{\alpha}\Delta^2 \Delta n_t)' n_t = \underbrace{\Delta lp_t' \Delta n_t}_{-} - \underbrace{\left(\frac{\Delta n_{t-1}' \Delta lp_t}{\Delta n_{t-1}' \Delta^2 n_t} \right) \Delta^2 n_t' \Delta n_t}_{+} < 0 \tag{3.7}$$

The covariance $\Delta lp_t'\Delta n_t$ is negative in the U.K. data. The negative covariance is consistent with the large negative correlation between labour productivity growth and hours growth (Table 1). Moreover, the covariances $\Delta n_{t-1}'\Delta lp_t$ and $\Delta n_{t-1}'\Delta^2 n_t$ are negative and $\Delta^2 n_t'\Delta n_t$ is positive. The overall effect of technology shock on hours is, therefore, negative.

3.4 Investment-specific technology shocks

The technology shocks identified above using the methodology described in Section 2 are *neutral* technology shocks. These shocks affect the production of all goods in the same way. Greenwood et al. (1997) and Greenwood et al. (2000), however, stress the importance of *investment-specific* technical change (as embodied only in new investment goods) relative to neutral technical change as a major source of economic growth. A shock to investment-specific technology affects the rate of transformation of current consumption into future productive capital. They point to the secular decline in the relative price of investment and a simultaneous increase in the relative production of investment goods in the post-war US data as indicative of investment-specific technical change.

Building of that framework, Fisher (2005) considers the empirical importance of investment-specific technology shocks (I-shocks) for US business cycles. A business cycle model with I-shocks predicts that hours and output should rise after a positive I-shock, similar to the responses of these variables to an N-shock. Fisher (2005) finds the estimated responses to be consistent with the predicted ones, and that such shocks are relatively more important than neutral technology shocks (N-shocks) as they account for a large proportion of the business cycle effects of technology shocks. Figure 9 shows the relative price of business investment (ratio of business investment deflator to the GDP deflator) in the UK. There is a downward trend since the late 1970s, and a sharp decline since the mid-1980s. Over the sample entire period, the relative price has declined, on average, by 55%. At the same time there has been an increase in the quantity of investment goods produced in the UK economy. These movements are similar to those in the US and suggest that I-shocks may also be important for UK business cycles.

Fisher (2005) uses two long run restrictions to identify the N- and the I-shocks. First, only shocks to investment-specific technology affect the relative price of investment in the long run. Second, only shocks to neutral or investment-specific technology affect labour productivity in the long-run. We consider the same methodology and identify the I- and the N-shocks for the UK using long-run identification.[21] The VAR specification (2.2) now includes the relative price of business investment. As noted in Fisher (2005), constructing a relative price of investment is challenging given the measurement problems with investment deflators, particularly those related to quality adjustments. We expect similar problems would arise in constructing the business investment deflator for the UK. To mitigate this problem we also consider an ICT deflator constructed by the Bank of England, which incorporates some quality adjustments. Moreover, the relative price of ICT has declined on average 345% over the sample period, a substantially larger decline than the relative price of business investment. We, therefore, consider the ICT deflator to be in line with the views of Greenwood et al. (1997).

Figure 10 shows the responses to both I- and N-shocks identified from a three-variable VAR. The responses of labour productivity, hours, and output to N-shocks are consistent with those in Figure 5. There is a statistically significant decline in hours after an N-shock. By contrast, in

[21] Here we do not impose an additional cross-equation restriction implied by the two identifying assumptions as discussed in Fisher (2005). The results from medium-run identification are qualitatively similar. Balleer (2004) investigates implications of medium-run identification to Fisher (2002) model using US data.

response to I-shocks, hours rise in a persistent hump-shaped manner. This response is statistically significant. Output also rises and exhibits a hump-shaped response, and is marginally significant over five to twelve quarters. Productivity, on the other hand, shows a persistent, and statistically significant, decline. Figure 11 shows the responses when we consider the ICT deflator instead of the business investment deflator to measure the relative price of investment. The main difference with respect to Figure 10 is that the response of output is statistically significant. The increase in output and hours upon impact is consistent with the prediction of a real business cycle model with such shocks. Table 4B presents the correlation between hours and output conditional on I-shocks. This correlation is large and positive similar to that in the data. The responses are also consistent with Fisher (2005)'s findings for the US for the sample period 1955 Q1 to 2000 Q4. The persistent decline in labour productivity after an I-shock is, however, stronger in the UK relative to the US. After an I-shock, labour productivity remains negative even after ten years. This appears to be inconsistent with theoretical response of labour productivity to I-shock where labour productivity initially falls, and then recovers slowly.

To check whether the estimated labour productivity response is sensitive to I-shocks identified from larger VARs we consider the additional variables as in Section 3.2. In the larger VAR, with nominal consumption-to-output and nominal investment-to-output ratios, labour productivity still appears to decline in a persistent manner. This response is statistically significant after ten quarters (Figure 12). As in the 3-variable VAR, hours rise. The response of output, however, is muted along with the responses of consumption and investment.

As Fernald (2005) cautions, breaks in the data can be a source of low-frequency correlations and substantially affect short-run estimated responses. Although we do not find a break in labour productivity, we do detect a statistically significant break in the mean of nominal investment-output ratio in 1991 Q3 (a decline in the mean in the post 1991 sample). We use the exponential F-test of Andrews and Ploberger (1994) to test for a break in the mean of the series. The value for the F-statistic for a break in the mean of I/Y equals 59.60 with a bootstrapped p-value of 0.15.[22] It is possible that the break identified in the I/Y ratio in the UK data may bias the responses to I-shocks in the larger VAR. We allow for this break and examine the responses. The low frequency correlation that matters in this case obtains between hours and the investment share. We find that

[22]Bootstrapped values are based on Diebold and Chen (1996).

the responses of investment and hours are the most sensitive when we identify I-shocks using the ICT deflator.[23]

Figure 13 shows that the estimated response of investment to an I-shock is negative (dotted line) when one does not allow for the break and uses long run identification. In contrast the response of investment is strongly positive (solid line) with a break and long run identification or with medium run restrictions (12-20 quarters and no break in I/Y imposed).[24] Moreover, in the larger VAR the responses of hours and labour productivity are sensitive to the investment deflators (Figure 14).[25] In the larger VAR, investment rises strongly in response to the I-shock. This is consistent with the theoretical response of investment to an I-shock. The hours response is, however, muted for the business investment deflator and significant only after five years, whereas it continues to display a statistically significant hump shape for ten quarters for the ICT deflator (Figures 14 and 15). The point estimates of labour productivity indicate a persistent decline. However, for the ICT deflator we find that the response of productivity is similar to that in Fisher (2005). Productivity starts to recover after ten quarters, and is close to zero after eight years.

Interestingly, as it turns out, both the recommendations of Erceg et al. (2005) and Christiano et al. (2005) to include nominal consumption-to-output and nominal investment-to-output ratios in the VARs, and the recommendation of Fernald (2005) to allow for breaks appear to be important in the context of examining the implications of estimated I-shocks for the UK.[26]

3.5 Discussion: plausibility of alternative models

To summarize, in the UK data hours worked decline in response to positive neutral technology shocks. We considered the important debates in the literature surrounding identification of technology shocks, stationarity of labour input, the labour input measures, small and large VAR specifications, and neutral versus investment-specific technology shocks. We found that for the UK,

[23]Since the end of the last UK recession (1991 Q3) total hours display a pronounced upward trend. Combined with the downward shift in the mean of the investment share results in a negative correlation that is reflected in the estimated responses.

[24]There is an interesting parallel between this result and the main result in Francis, Owyang and Roush (2005) which concerns the level vs. difference hours debate in the U.S. Francis, Owyang and Roush (2005) using finite (medium run) restrictions show that the response of hours to a positive (neutral) technology shock is negative even if hours enter in levels.

[25]We have also experimented using the US investment price series from Fisher (2005), and the NIPA ICT investment deflators (using UK nominal investment shares and the nominal exchange rate). The results were in both cases qualitatively similar to the ones we obtained using the UK ICT deflator.

[26]The response of hours in Section 3.3 is robust to this break in the I/Y ratio.

the response of hours worked does not change, ie., hours *always decline* after a (neutral) technology shock. The negative covariance (as evident in the large negative correlation) between labour productivity and hours in the UK data drives this response. The robustness of the response to the important debates in the literature suggests that the UK economy offers an unique perspective on the debate on the response of hours to estimated technology shocks.

We provide a brief discussion on the plausibility of alternative models for interpreting the response of hours in the UK data, and more generally for investigating the role of technology shocks for business cycle issues.

3.5.1 RBC versus sticky-price model

Our results can help assess the plausibility of alternative models for understanding the role of technology shocks in UK business cycles. The response of hours worked to identified technology shocks in the data is not consistent with the standard RBC model which predicts a rise in hours worked. Prediction of a sticky price model, however, can be consistent with a decline in hours worked as stressed in Galí (1999). When prices are sticky, a positive technology shock lowers firms' marginal cost (increases markup), so a given level of demand can be met with reduced number of hours worked. The reduction in hours would occur even if aggregate demand rises due to monetary expansion, as long as the increase is proportionally less than the increase in productivity.[27]

Francis and Ramey (2004), on the other hand show that flexible price models augmented to include real rigidities such as habit-formation and capital adjustment costs can also rationalize the decline in hours.[28] Given the persistent decline in hours worked in the UK, it is, however, difficult to gauge whether real frictions of this sort are particularly strong in the UK economy.[29]

Another dimension that favours the sticky-price model is the muted response of investment after a positive (neutral) technology shock. While this response is difficult to rationalize within an RBC model, which predicts a strong rise in investment, it can be rationalized within a sticky price model as discussed in Basu et al. (2005).

[27] Liu and Phaneuf (2004) show that a sticky wage model, relative to a sticky price model, can better account for real and nominal wage responses as well to technology shocks.

[28] See also, for example, Lindé (2004).

[29] Groth (2005) finds that estimated capital adjustment costs in the UK are broadly similar to those found for the US in the literature.

3.5.2 Open-economy RBC model with real rigidities

Recently, Collard and Dellas (2004) show that an open economy RBC model in which the elasticity of substitution between domestic and foreign consumption is sufficiently low can generate a decline in hours after a technology shock. This model appears to be useful for interpreting the hours response for two reasons. First, open-economy models are generally regarded as more relevant for the UK economy and, second, the estimates of trade elasticities for the UK as reported in Hooper et al. (2005) are quite small (and in the range where the Collard and Dellas (2004) model predicts a decline in hours). We considered both the real exchange rate and the trade balance (in first-differences) in the larger VAR of Section 3.2.[30] Figures 16 and 17 show the results for the two cases, respectively. In response to technology shocks, real exchange rate depreciates in a persistent manner. The response is statistically significant after a few quarters. Net exports decline and recover slowly, although the response is not significant. Qualitatively, these conditional responses are in line with those in Collard and Dellas (2004).

However, as cautioned by Erceg et al. (2005), the SVAR framework is suitable for discriminating between models that have sufficiently divergent implications, and in the present context, about how technology shocks affect the labour market. From this perspective, it may be difficult to distinguish between sticky price models and the open economy RBC models with imperfect substitutability between domestic and foreign consumption goods. Both models predict a decline in hours after a technology shock.

3.5.3 RBC model with investment-specific shocks

Investment-specific technology shocks generate a positive co-movement between hours and output, and a negative co-movement between productivity and hours. This pattern of conditional correlations does resemble the unconditional correlations between the same variables in the UK data. In addition, after an I-shock, investment appears to rise.

Overall, we conclude that price stickiness, low substitutability between domestic and foreign consumption, and investment-specific shocks appear to be the most relevant features in interpreting and investigating the short-run effects of technology shocks on hours, output, and investment. We now turn to a quantitative evaluation of technology shocks for UK business cycles.

[30] Trade balance is defined as the value of net UK exports to the world. The real exchange rate is with the major six trading partners, with an increase denoting an appreciation.

4 Do technology shocks drive UK business cycles?

In this section we assess whether technology shocks (both neutral and investment-specific) are important drivers of UK business cycles. We examine the role of technology shocks in the variability of hours and output based on small and large VARs considered in Section 3. We also examine the contributions of these shocks to the UK business cycle.

4.1 Forecast error decompositions

Table 5 reports the percent of forecast error variance due to technology and non-technology shocks, at horizons 1, 4, 8, 12, 20, and 50 quarters based on the bivariate VAR (with hours in level). Technology shocks account for a small fraction of the variance of output until twelve quarters, and account for a small fraction of the variance of hours at all horizons. For example, they account for approximately 10% and 15% of the twelve-step-ahead forecast error variance in hours and output, respectively. By contrast, in the US data, technology shocks account for approximately 45% and 90% of the forecast variance in hours and output at a twelve-quarter horizon (see Christiano et al. (2003)). In a larger VAR, as shown in Table 6, technology shocks account for a somewhat higher fraction of the variance in hours and output relative to bivariate VAR. For example, they account for approximately 17% and 16% of the twelve-step-ahead forecast error variance in hours and output, respectively.

Table 7 presents the forecast error decompositions for I-shocks and N-shocks. The I-shocks contribute more to the forecast error variance of hours than the N-shocks over horizons of four to twenty quarters. The contribution of I-shocks is, however, less than 35%. The N-shocks contribute relatively more to the forecast error variance of output over horizons of four to twenty quarters. The contributions of these horizons, however, remain less than 30%. Comparing it with the results in Fisher (2005) for the US, we find that the qualitative pattern of contributions of I- and N-shocks to the forecast error variance of hours and output is similar. However, in quantitative terms the percent contributions of both shocks are smaller at these horizons. For example, in the US, I-shocks account for 57% of the variance in hours and 35% of the variance in output at a twelve-quarter horizon, whereas N-shocks, 14% and 61%, respectively. In the UK, I-shocks account for approximately 26% of the variance in hours and 13% of the variance in output, whereas N-shocks, 2% and 29%, respectively.

4.2 Contributions to UK business cycles

We examine the relative business cycle variance of variables due to technology shocks. The relative variance of a variable x is given as $V(x^v)/V(x^d)$ where $V(x^v)$ is the variance of the business cycle components (HP filtered) of simulated data obtained from the VAR driven only by the estimated technology shocks and $V(x^d)$ is the variance cyclical component of the actual data. This ratio provides an estimate of the fraction of business cycle variation in a particular variable due to technology shocks. Table 8 reports the business cycle effects when only N-shocks are identified using both small and large VARs. The relative variance of output and hours is less than 25%. Similarly, the relative variance of investment and consumption is even smaller, under 13%.

Table 9 presents the relative business cycle variance of I- and N-shocks. The estimates based on smaller VAR imply that I-shocks account for 15% of the business cycle variation in hours compared to N-shocks which account for only 2%. On the other hand, N-shocks account for about 18% of the variance output compared to the I-shocks which account for about 10%. In the larger VARs (with either the business investment deflator or the ICT deflator based relative price of investment), the N-shocks appear to account for a relatively higher fraction of business cycle variation in output and hours than the I-shocks. The I-shocks account for 20% to 30% of the business cycle variability in investment and about 6% to 10% of the cyclical variability in consumption. These magnitudes for consumption and investment are higher than those accounted for by the N-shocks.

In comparison with Fisher (2005), we find that the relative cyclical variances of hours and output accounted for by N-shocks in the UK are small and similar in magnitude as those in the US data. The cyclical variances accounted for by I-shocks are, however, substantially smaller compared to those in the US data.[31] Overall, our quantitative results suggest that technology shocks (either neutral or investment-specific) play a limited role as drivers of UK business cycles.

[31] Note that we have specified total hours in levels. In the US data, when total hours (or any other measure of labour input) enter the VAR in levels, the contribution of I-shock to business cycle variability of output and hours is the larger than when the labour input enters the VAR in first-difference or is detrended. See, for example, Galí and Rabanal (2004) Table 3. When we consider first-difference hours for the UK, the contribution of I-shock to business cycle variability of hours and output is even smaller relative to the level specification.

5 Robustness analyses

In this section we conduct a variety of robustness checks and provide corroborative evidence to establish that the permanent shocks to labour productivity in the UK data identified as technology shocks in Section 3 are indeed capturing variations in technology. We also discuss the robustness of our findings to sub samples.

5.1 Technology, Solow residuals, and tax rate correlations

We examine correlations between identified technology shocks and an alternative measure of technology (the Solow residual), innovations to dividend income tax, and correlations of permanent shock to productivity across various VAR specifications. Table 10 presents the correlations between the identified technology shocks from the VAR systems with (i) the Solow residual, which is an alternative measure of technology based on a growth-accounting methodology, and (ii) the UK dividend tax rate as calculated in McGrattan and Prescott (2004). The UK Solow residual is taken from Groth et al. (2005). It is a private (non farm) sector measure that controls for aggregation effects building up from an industry-based analysis. It uses the capital services measure and corrects for labour quality.[32] The correlation between identified permanent shocks to labour productivity and the Solow residual is relatively large for the quarterly data (approximately 0.5). This strong correlation between two different measures of technology shock supports the interpretation of identified permanent shocks to productivity as technology shocks.[33]

As discussed in Uhlig (2004), a leading non-technology variable which may potentially influence labour productivity in the long run is the capital income tax rate. Permanent shifts in capital income tax rate will affect the capital-labour ratio and hence labour productivity. To evaluate this hypothesis we compute correlations in Table 10.[34] The correlation with dividend income tax shock

[32]The measure of Solow residual, however, does not control for variable utilization of inputs and non-constant returns as in Basu et al. (2005).

[33]The correlation between the Solow residual constructed in Basu et al. (2005) and the permanent shocks to productivity, as reported in Galí (2004), is 0.45. As an additional check, using the historical UK data (1855-2001) from Francis and Ramey (2005) we identify permanent shocks to labour productivity via long-run restrictions, and compute the corresponding correlations. The correlation between the Solow residual and technology shock is very strong, 0.88, for the historical data.

[34]We use the dividend tax rate as computed in McGrattan and Prescott (2004), covering the period 1919 - 2000. We cannot reject the null of a unit root in this series and given no significant autocorrelation of its first differences, we take the latter as our measure of the tax rate shock. A similar measure is considered in Galí (2004).

is negative for permanent shocks identified from the different VAR specifications in both quarterly and historical data for the UK.

An additional dimension that we have considered is the possibility that the identified technology shocks may be contaminated with labour supply shocks. For example, the estimated responses to productivity and hours we obtain could be consistent with a *contractionary* labour supply shock. To evaluate this hypothesis we have considered a specification that includes the GDP deflator as a measure of the price level. A simple test for evaluating this hypothesis is to examine the response of the price level following a positive technology shock. The response of the GDP deflator we obtain (not shown) shows that the price level declines (significantly) thus being inconsistent with the prediction of a contractionary labour supply shock.[35] Taken together, the findings in Table 10 suggest that the identified shocks do appear to be capturing variations in technology.

5.2 Contemporaneous correlations between identified shocks

We examine two sets of contemporaneous correlations between identified shocks. First, shocks identified using small and larger VARs. As advocated by Sims (1980) and Faust and Leeper (1997), checking the consistency of results in this manner is a useful exercise when conducting identification of shocks using VARs. Second, shocks identified using historical UK data and the quarterly UK data. In the long run data, technology shocks may be the single dominant source of the stochastic trend in labour productivity. For the UK data, the negative correlation with dividend income tax documented in Section 5.1 supports this hypothesis. If long-run identification is most robust for this (truly) long run dataset then examining correlations of identified shocks with those from the (shorter) quarterly data may strengthen the interpretation of shocks in the latter data as technology shocks.[36]

[35] If labour supply shocks are a dominant source of fluctuations in our sample (and thus confounds the implications drawn) we should obtain an increase in the price level. In contrast to a positive technology shock a contractionary labour supply shock should also lead to a reduction in output. This prediction on prices and output obtains under both classes of models we seek to distinguish.

[36] This rationale derives from discussion in Campbell and Perron (1991) on unit roots which emphasizes the span of the data as most important for the power of unit root tests rather than the number of observations. We also used medium-run restrictions on the historical data to back out the most persistent changes in labour productivity without imposing a unit root and checked the contemporaneous correlation between these identified shocks and those under long-run restriction. The correlation between permanent shocks to labour productivity under both identification schemes is 1. Moreover, the correlation between permanent and transitory shocks to productivity is approximately zero. This establishes that both types of restrictions provide identical answers.

Table 11 shows the correlations between shocks from small and larger VARs. The correlations between permanent shocks to labour productivity are high. This is consistent with the results in Section 4 which show that the responses to technology shocks estimated from small and larger VARs are similar. Table 12 presents correlations between shocks from the quarterly data and the historical data (for the same period as the quarterly data 1971 Q1 - 2004 Q4).[37] The correlation between the technology shocks from the historical and those from various VAR specifications estimated on the quarterly data are large and positive. Moreover, the correlation between the permanent shocks from the short sample and the transitory (non-technology) shocks (to productivity) in the historical sample is negative and close to zero. These correlations strengthen the interpretation of shocks in the quarterly data as technology shocks

5.3 Pre- and post-1992 data

We have shown that the negative correlation (and covariance) between productivity and hours drives the impulse response of hours to a positive technology shock. One source of the large unconditional negative correlation between labour productivity and hours documented in Table 1 may be measurement error in the pre-1992 UK labour input data which is interpolated on annual data. Table 13 reports the business cycle stylized facts for the sub-periods. In the post-1992 data the negative correlation between labour productivity and labour input measures is larger as compared to that in the pre-1992 data. This suggests that potential measurement error in the pre-1992 data is not driving the negative correlation in the sample.[38] Notice that labour productivity exhibits less procylicality in the post-1992 data. Its contemporaneous correlation (for the hours measure) with cyclical output and output growth are 0.14 and 0.36, respectively. In comparison, the correlations are 0.41 and 0.84, respectively, for the pre-1992 data. These correlations suggests that UK business cycles may have become somewhat muted since the early 1990s consistent with findings of Stock and Watson (2002).

[37] We use the employment measure of labour input since historical data on hours is not available. The shocks are annualized by averaging the shocks for each year.

[38] Wen (2004), who also documents a contemporaneous correlation of -0.12 between labour productivity and employment for the UK over the period 1960 Q1 - 1996 Q4, finds that the negative contemporaneous correlation arises because productivity leads employment by four quarters in the UK data.

6 Conclusion

In this paper we conducted an extensive investigation of responses of labour input to identified neutral and investment-specific technology shocks in the UK. Our main finding is that after a (positive) neutral technology shock hours worked decline in the UK data. We considered several important debates in the recent literature, namely, the measures of labour input, stationarity assumptions, identification schemes, VAR specifications, and neutral versus investment-specific technology shocks. The response hours is robust across all of the above considerations. Our finding, therefore, suggests that the UK economy offers a unique perspective on the debate on the response of hours to technology shocks. The large negative correlation between labour productivity and hours is the source of this negative response of hours. Investment-specific shocks generate a positive co-movement between hours and output, and raise investment, both consistent with the data and the theoretical responses. However, these findings appear to be sensitive across larger VAR systems and trend breaks. Overall, the findings suggest that models with price stickiness, low substitutability between domestic and foreign consumption, and investment-specific shocks appear to be most plausible in accounting for the short-run effects of technology shocks on hours, output, and investment. Quantitatively, however, technology shocks account for under 20% of the business cycle variation in hours and under 30% of business cycle variation in output. These findings suggest that technology shocks may play only a limited role in driving UK business cycles.

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Table 1
UK: Key business cycle facts (1971 Q1 - 2004 Q4)

	Output		Hours		Employment		Labor prod.	
	HP	Δ	HP	Δ	HP	Δ	HP	Δ
			Whole economy measures					
Output	1	1						
Hours	0.69	0.35	1	1				
Labour prod.	0.37	0.80	**-0.40**	**-0.27**			1	1
Output	1	1						
Employment	0.54	0.34			1	1		
Labour prod.	0.70	0.90			**-0.22**	**-0.09**	1	1
			Private sector measures					
Output	1	1						
Hours	0.87	0.57	1	1				
Labour prod.	-0.14	0.35	**-0.60**	**-0.56**			1	1
Output	1	1						
Employment	0.82	0.59			1	1		
Labour prod.	0.30	0.58			**-0.30**	**-0.31**	1	1

HP refers to Hodrick-Prescott Filter ($\lambda = 1600$). Δ indicates first difference.

Table 2

Stationarity tests: uk labour input measures

	Whole economy		Private sector	
	ADF	KPSS	ADF	KPSS
Labor productivity (output per hour)	-2.7		-2.5	
	(0.23)		(0.32)	
Labor productivity (output per worker)	-2.2		-2.72	
	(0.48)		(0.23)	
Per capita hours (constant)	-2.43	0.70†	-4.26	0.08*
	(0.13)		(0.001)	
Per capita hours (constant+trend)	-2.61	0.21†	-4.26	0.07*
	(0.27)		(0.006)	
Total hours(constant)	-2.57	0.32*	-2.41	0.52†
	(0.10)		(0.14)	
Total hours (constant+trend)	-2.89	0.18†	-4.12	0.09*
	(0.16)		(0.009)	
Employment (constant+trend)	-2.49	0.17†	-3.49	0.11*
	(0.32)		(0.04)	
Per capita Employment (constant)	-2.26	0.22*	-2.87	0.52†
	(0.18)		(0.05)	

ADF and KPSS tests are based on a constant or constant and linear time trend as indicated. Selection of lags in the ADF test equations are based on SIC criteria. p-values for null of a unit root in parenthesis for ADF test.

* (†) indicate that the KPSS test does not reject (rejects) null of stationarity at the 10% level. Hours are divided by population age 16 and older.

Table 3

UK: Annual Data (1970-2003)

	Output		Hours		Labor prod.	
	HP	Δ	HP	Δ	HP	Δ
	Whole economy measures					
Output	1	1				
Hours	0.85	0.76	1	1		
Labour prod.	-0.16	0.06	-0.66	-0.59	1	1

HP refers to Hodrick-Prescott Filter ($\lambda = 1600$). Δ indicates first difference.

Table 4A

conditional correlations: between labour productivity (growth) and labour input

	Technology	Non technology
Differenced hours† (whole-economy)	-0.99	0.09
Differenced hours† (private-sector)	-0.99	0.08
Detrended employment* (whole-economy)	-0.32	0.53
Detrended employment* (private-sector)	-0.29	0.32

† Row 1 corresponds to Figure 3. Row 2 to Figure 4. 2 lags in VAR.

Table 4B

conditional correlations: between business cycle component of output and hours

	Neutral Technology	Investment Specific	Non technology
Fig.5	-0.43		0.84
Fig.11	-0.60	0.92	

† Row 1 corresponds to Figure 5. Row 2 to Figure 11. HP filtered data.

Table 5

forecast error decompositions: technology (t) and non-technology (nt) shocks

	Horizon (quarters)					
Variable	1	4	8	12	20	50
	T, NT	T, NT	T, NT	T, NT	T, NT	T, NT
Productivity	74.2, 25.7	80, 20.0	97.2, 2.7	99.2, 0.4	99.6, 3.3	99.1, 0.0
Hours	36.7, 63.3	18.6, 81.3	12.3, 87.7	10.3, 89.6	8.7, 91.2	8.2, 91.7
Output	29.6, 70.3	7.1, 92.8	5.0, 94.9	14.5, 85.4	84.9, 15.0	100, 0

VAR(4). Hours in level.

Table 6

forecast error decompositions: technology shock

	Horizon (quarters)					
Variable	1	4	8	12	20	50
Productivity	63.9	83.2	95.6	99.0	98.2	99.1
Hours	42.5	31.3	23.0	16.9	8.8	6.3
Output	0.1	18.1	35.5	16.3	32.0	99.1
Inflation	34.6	42.6	51.7	59.4	66.2	58.2
Real rate	4.9	13.6	12.6	4.0	11.0	11.4

VAR(5). Hours in level.

Table 7

forecast error decompositions: investment specific (is) and neutral (n) technology shocks

	Horizon (quarters)					
Variable	1	4	8	12	20	50
	IS, N	IS, N	IS, N	IS, N	IS, N	IS, N
RPI	76.6, 2.7	78.1, 3.1	76.2, 1.4	78.5, 0.8	87.7, 0.3	99.0, 0.0
Productivity	5.3, 74.7	4.5, 81.0	11.0, 87.8	18.0, 81.8	26.7, 70.8	28.1, 71.3
Hours (level)	16.4, 19.8	15.7, 7.0	20.5, 2.8	25.8, 1.8	34.4, 1.1	42.1,1.0
Output	65.5, 33.5	5.3,18.2	12.6, 14.5	13.3, 28.4	0.2, 94.0	27.3, 72.6

VAR(4), 4 lags, RPI=Relative price of total business investment.

table 8: business cycle effects (N shocks)

relative volatility

	$V(y^v)/V(y^d)$	$V(h^v)/V(h^d)$	$V(i^v)/V(i^d)$	$V(c^v)/V(c^d)$	$V(\pi^v)/V(\pi^d)$	$V(r^v)/V(r^d)$
Var(4)	0.14	0.07	-	-	-	-
Var(3)	0.08	0.25	0.10	0.05	-	-
Var(5)	0.25	0.22	-	-	0.32	0.24
Var(3)	0.22	0.13	0.13	0.11	0.11	0.13

N shocks = neutral technology shocks.

TABLE 9: BUSINESS CYCLE EFFECTS

RELATIVE VOLATILITY

	Var(4)		Var(4)*		Var(4)**	
	IS	N	IS	N	IS	N
$V(y^v)/V(y^d)$	0.10	0.18	0.07	0.08	0.07	0.12
$V(h^v)/V(h^d)$	0.15	0.02	0.02	0.21	0.05	0.37
$V(i^v)/V(i^d)$	-	-	0.32	0.04	0.23	0.09
$V(c^v)/V(c^d)$	-	-	0.06	0.01	0.10	0.0

IS= Investment specific. * Total business investment deflator. ** ICT deflator.

TABLE 10

CORRELATIONS

	1971 Q1 - 2004 Q4			
	Tech1	Tech2	Tech3	Tech4
Tax	-0.16	-0.42	-0.40	-0.39
Solow resid.	0.58	0.30	0.30	0.42
Historical (Francis and Ramey (2002) dataset)				
	Tech.	Solow resid.	Non tech.	Tax†
Tech.	1			
Solow resid.	0.88	1		
Non tech.	0.0	0.16	1	
Tax	-0.2	0.01	0.09	1

Identified shocks from VAR(4) historical data, and long-run restriction.

† Tax is first difference of dividend tax rate. Tech1 and Tech2 are identified neutral technology shocks obtained from Fisher (2005) VARs in 3 and 5 variables. Tech3 and Tech4 are identified neutral technology shocks obtained from extended type VARs in 4 and 6 variables. Annual averages used for quarterly data.

TABLE 11

CORRELATIONS: SHOCKS FROM SMALL VS. LARGER VARS

	Tech1.	Tech2.	Tech3.	Nontech1
Tech1.	1			
Tech2.	0.87	1		
Tech3.	0.94	0.85	1	
Nontech1.	0.008	-0.20	-0.06	1

† Row 1:VAR(4) in productivity, hours (level), long run

Row 2: VAR(3) in productivity, hours (level), I/Y and C/Y ratios, long run.

Row 3: VAR(5) in productivity, hours (level) plus real interest rate and inflation rate (all quadratic detrended).

Nontech1 is the "other" shock corresponding to Tech1.

Annual averages used.

TABLE 12

CORRELATIONS: TECHNOLOGY SHOCKS FROM DIFFERENT SAMPLES

		Historical	
1971 Q1 - 2004 Q4		Tech.	Non Tech.
	Tech6.	0.52	-0.07
	Tech4.	0.40	-0.09
	Techempl	0.62	0.02

† UK historical: VAR(4) in (employment,productivity), quadratic trend removed, long-run ident.

Short sample. Row 1: VAR(3) in productivity, hours(levels) inflation and real rate (both quadratically. detrended).

plus i/y and c/y ratios. Long-run ident.

Short sample. Row 2: VAR(3) in productivity, hours(levels) plus i/y and c/y ratios. Long-run ident.

Short sample. Row 3: VAR(3) in productivity, employment,plus i/y and c/y ratios. Long-run ident.

Annual averages used for short sample

Table 13

UK: Key business cycle facts: whole economy measures

		Output		Hours		Employment		Labor prod.	
		HP	Δ	HP	Δ	HP	Δ	HP	Δ
Output		1	1						
Hours	Pre-92	0.69	0.41	1	1				
	Post-92	0.73	0.03	1	1				
Labour prod.	Pre-92	0.41	0.84	**-0.36**	**-0.13**			1	1
	Post-92	0.14	0.36	**-0.56**	**-0.81**			1	1
Output		1	1						
Employment	Pre-92	0.51	0.35			1	1		
	Post-92	0.71	0.19			1	1		
Labour prod.	Pre-92	0.72	0.91			**-0.21**	**-0.05**	1	1
	Post-92	0.55	0.76			**-0.19**	**-0.48**	1	1

HP refers to Hodrick-Prescott Filter ($\lambda = 1600$). Δ indicates first difference.

Figure 1: Labor market data

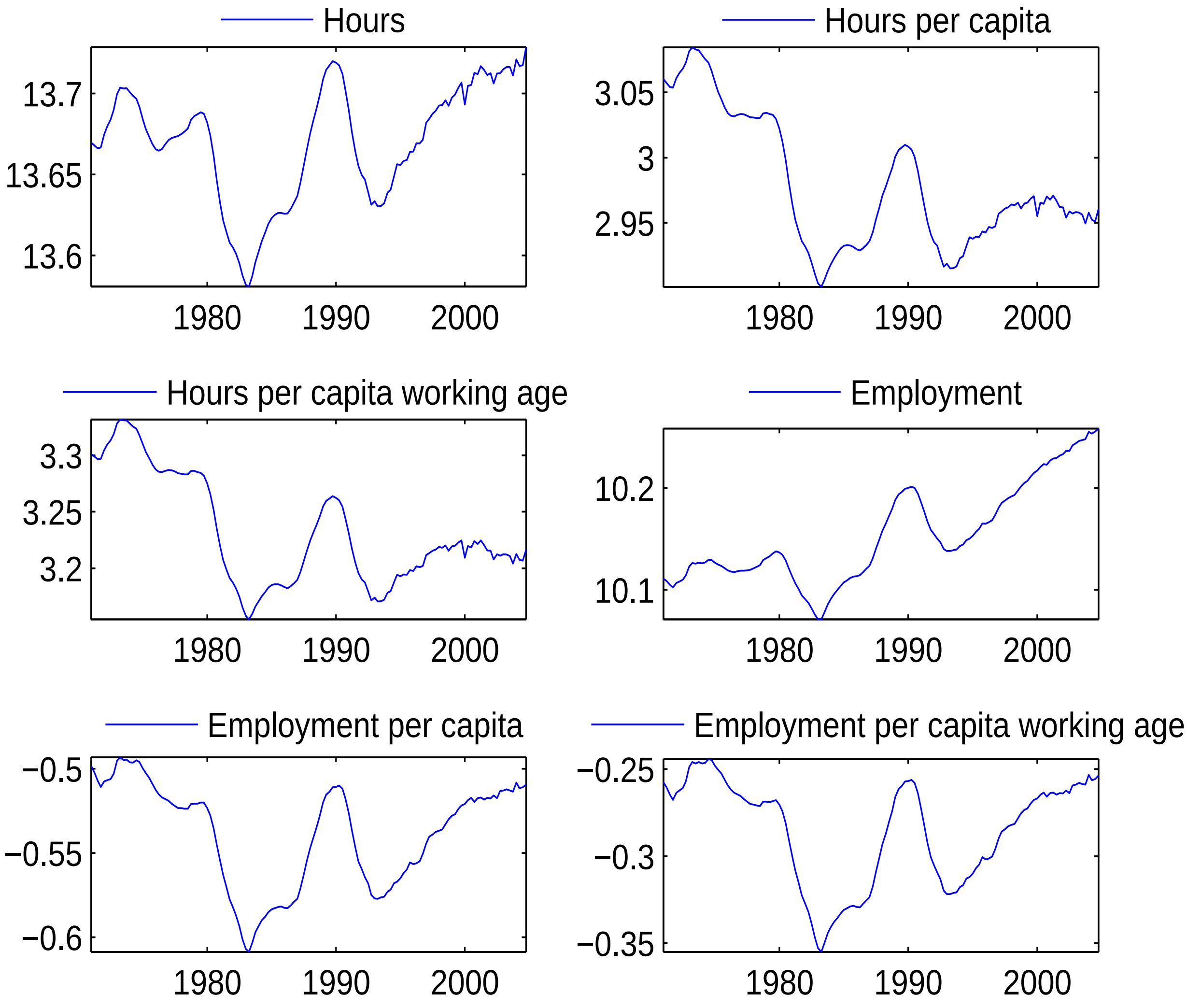

Figure 2: Quarterly data

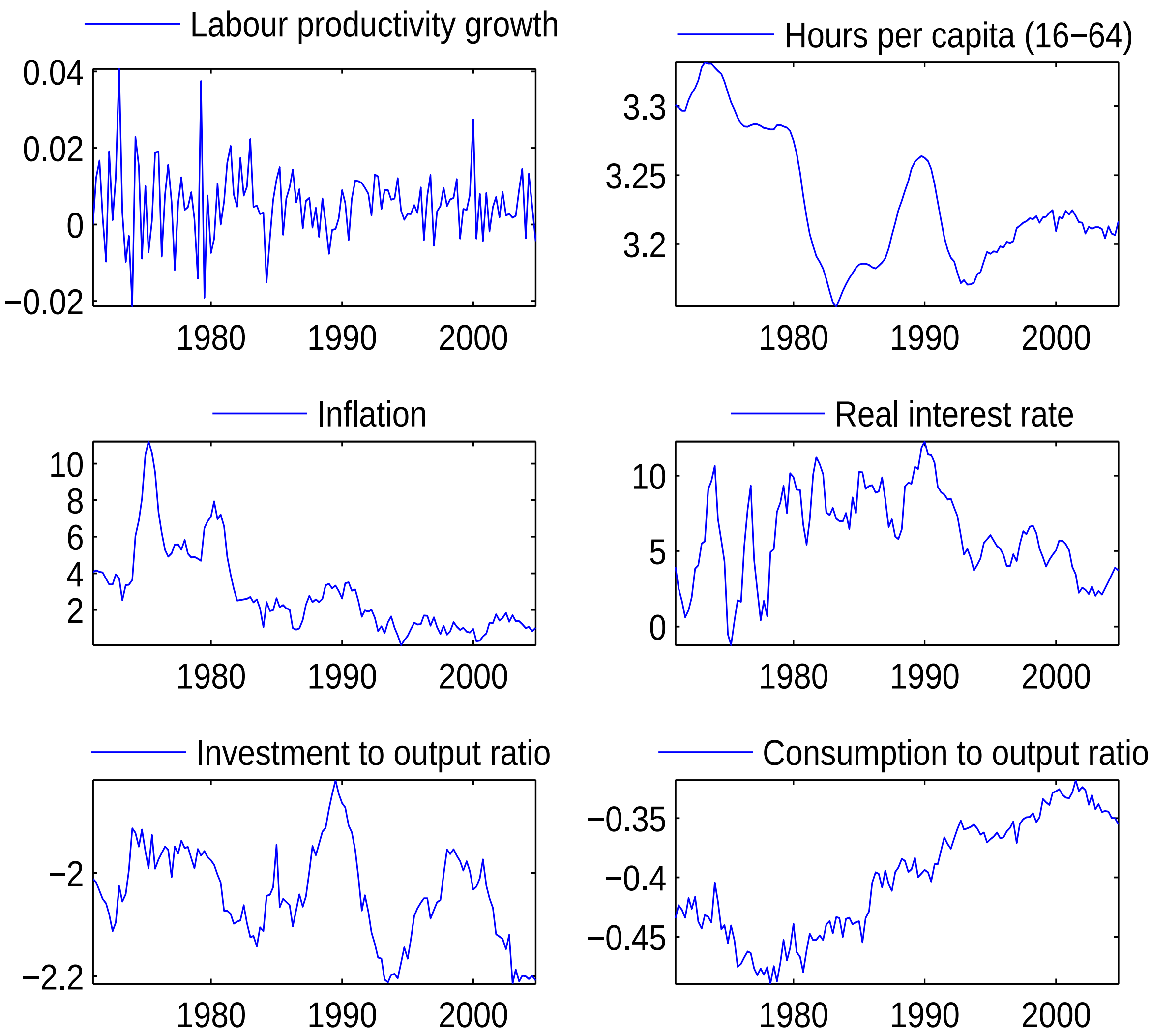

Figure 3: UK: Whole economy, differenced total hours, 2 lags in VAR, Technology shocks (left column), Non-technology shock (right column)

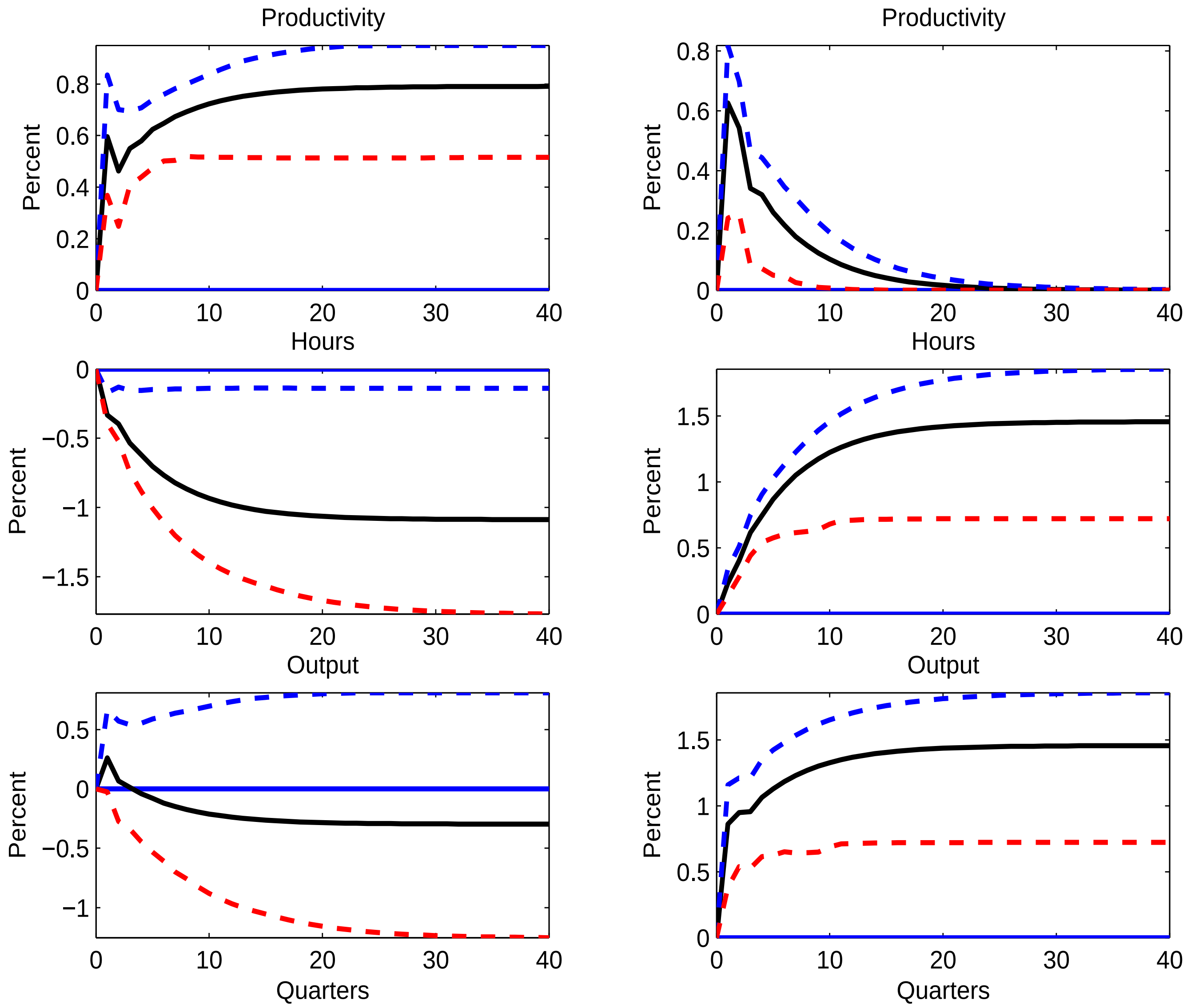

Figure 4: UK: Private sector, differenced hours, 2 lags in VAR, Technology shocks (left column), Non-technology shock (right column)

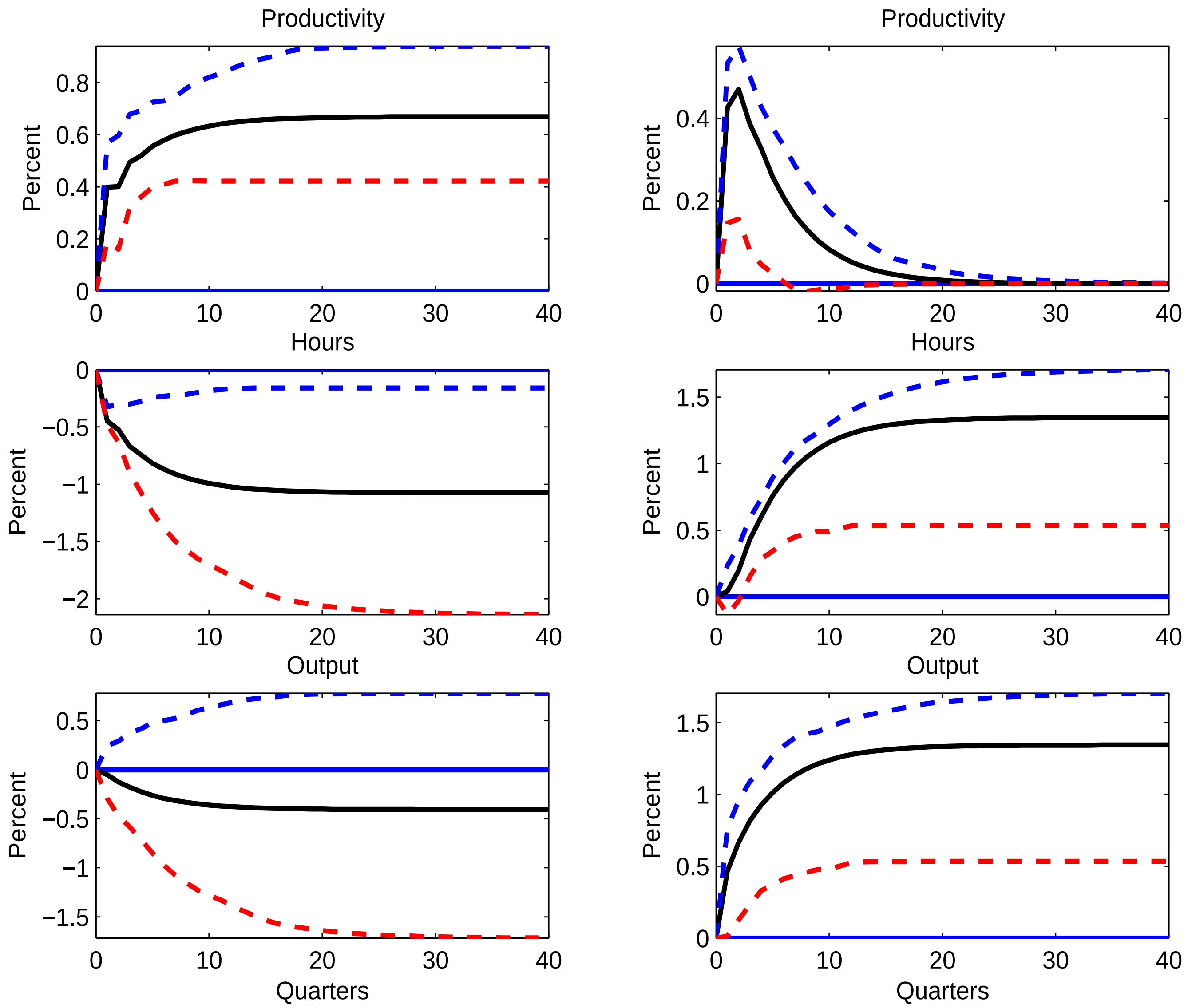

Figure 5: UK: Whole economy, hours in levels, 4 lags in VAR, Technology shocks (left column), Non-technology shock (right column)

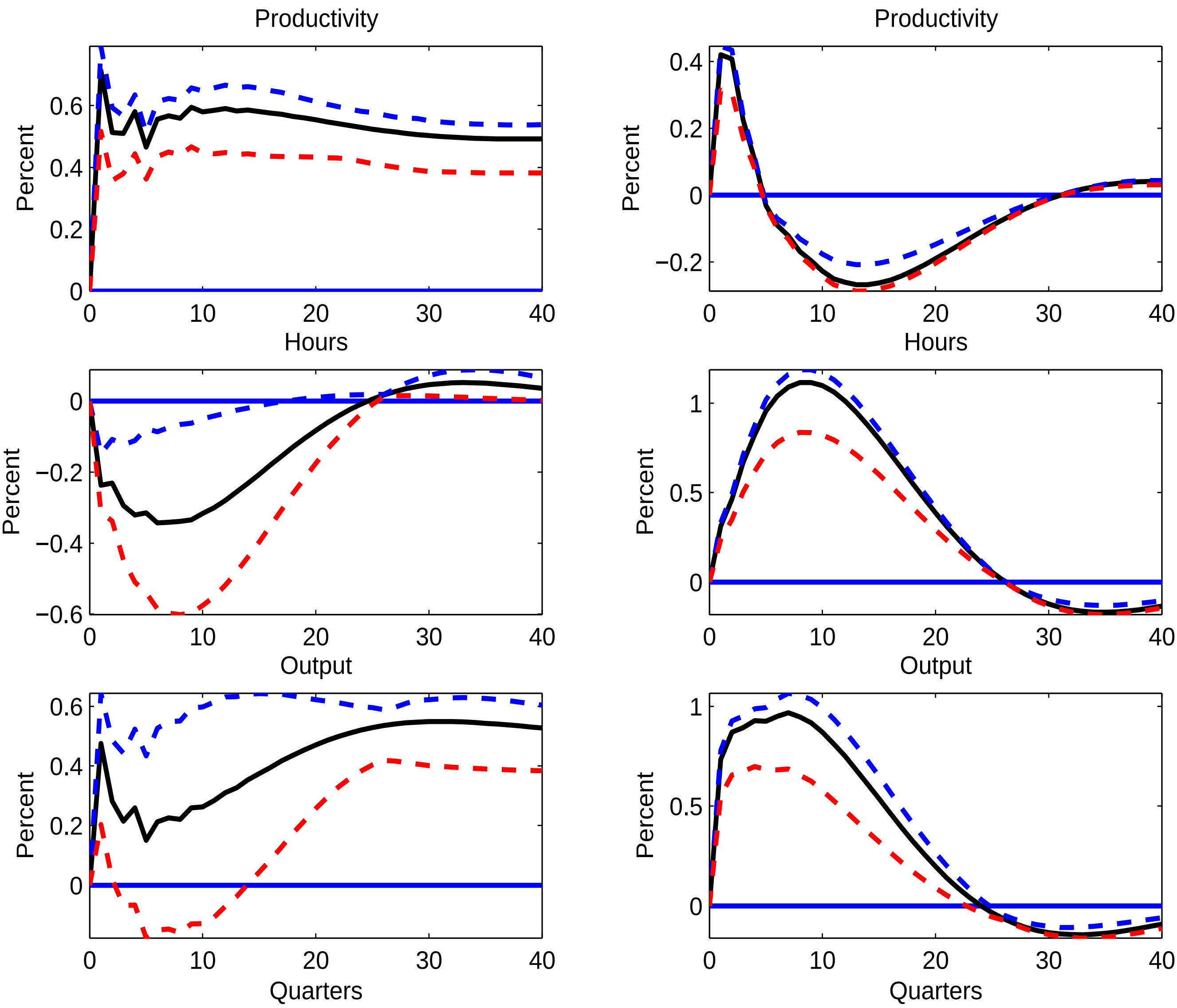

Figure 6: UK: Private sector, level hours, 3 lags in VAR, Technology shocks (left column), Non-technology shock (right column)

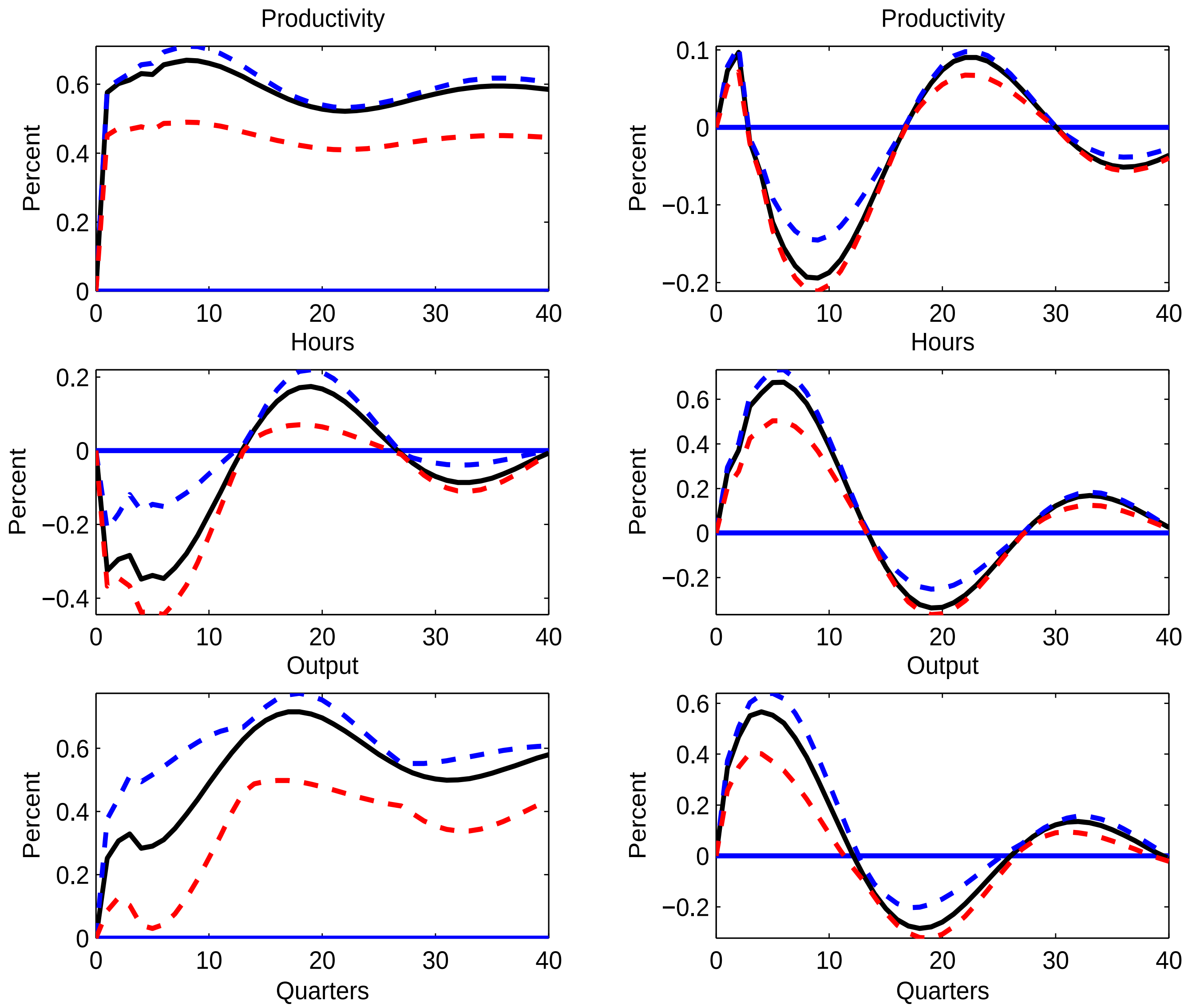

Figure 7: UK: whole-economy, level hours, four-variable VAR, four lags, medium-run identification

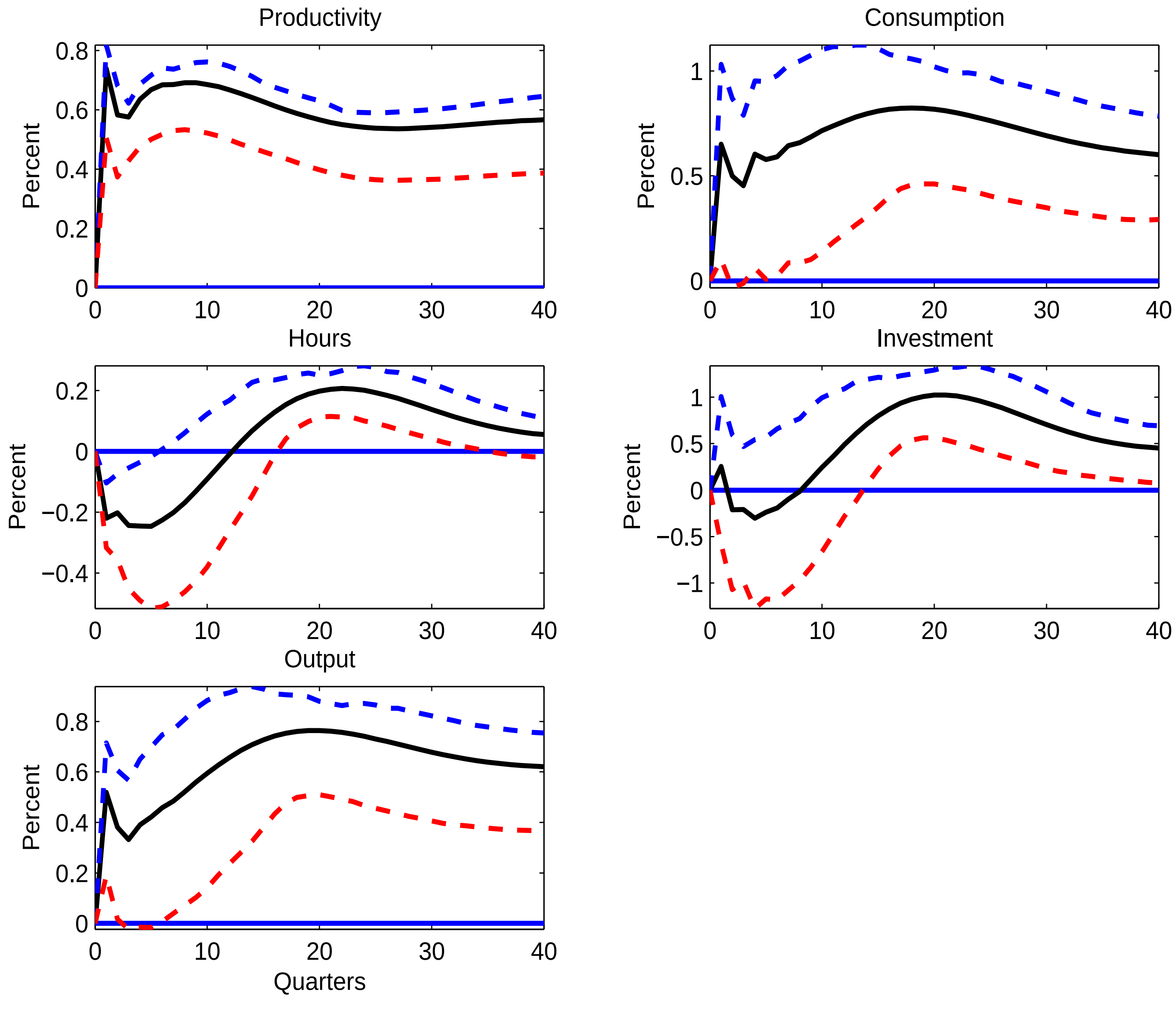

Figure 8: UK: whole-economy, level hours, six-variable VAR, four lags, medium-run identification

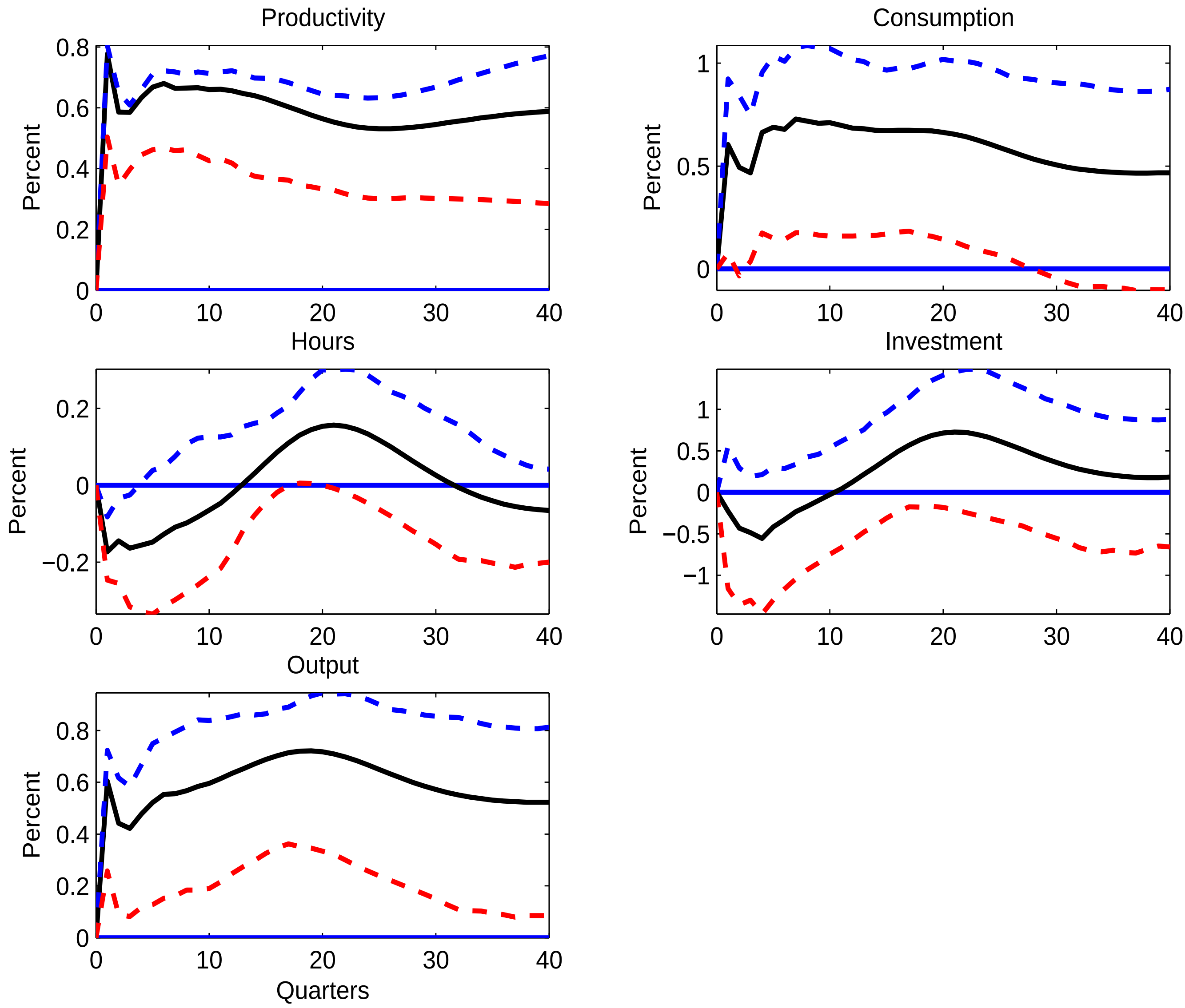

Figure 9: Relative price (P_I/P_Y) and real share of business investment

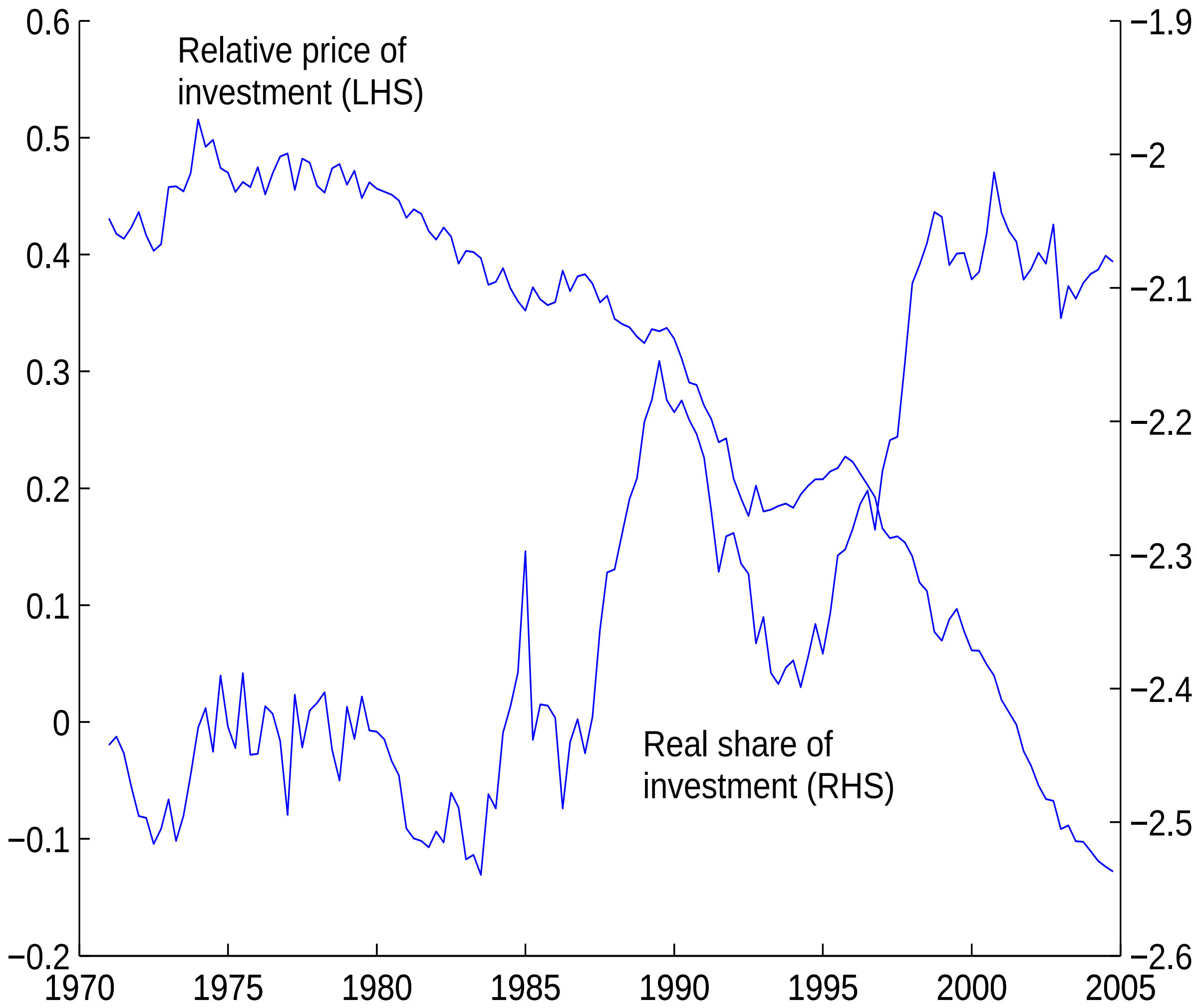

Figure 10: UK: whole economy, 4 lags in VAR, level-hours, long run restrictions, **investment-specific technology shock** (left column), **neutral technology shock** (right column)

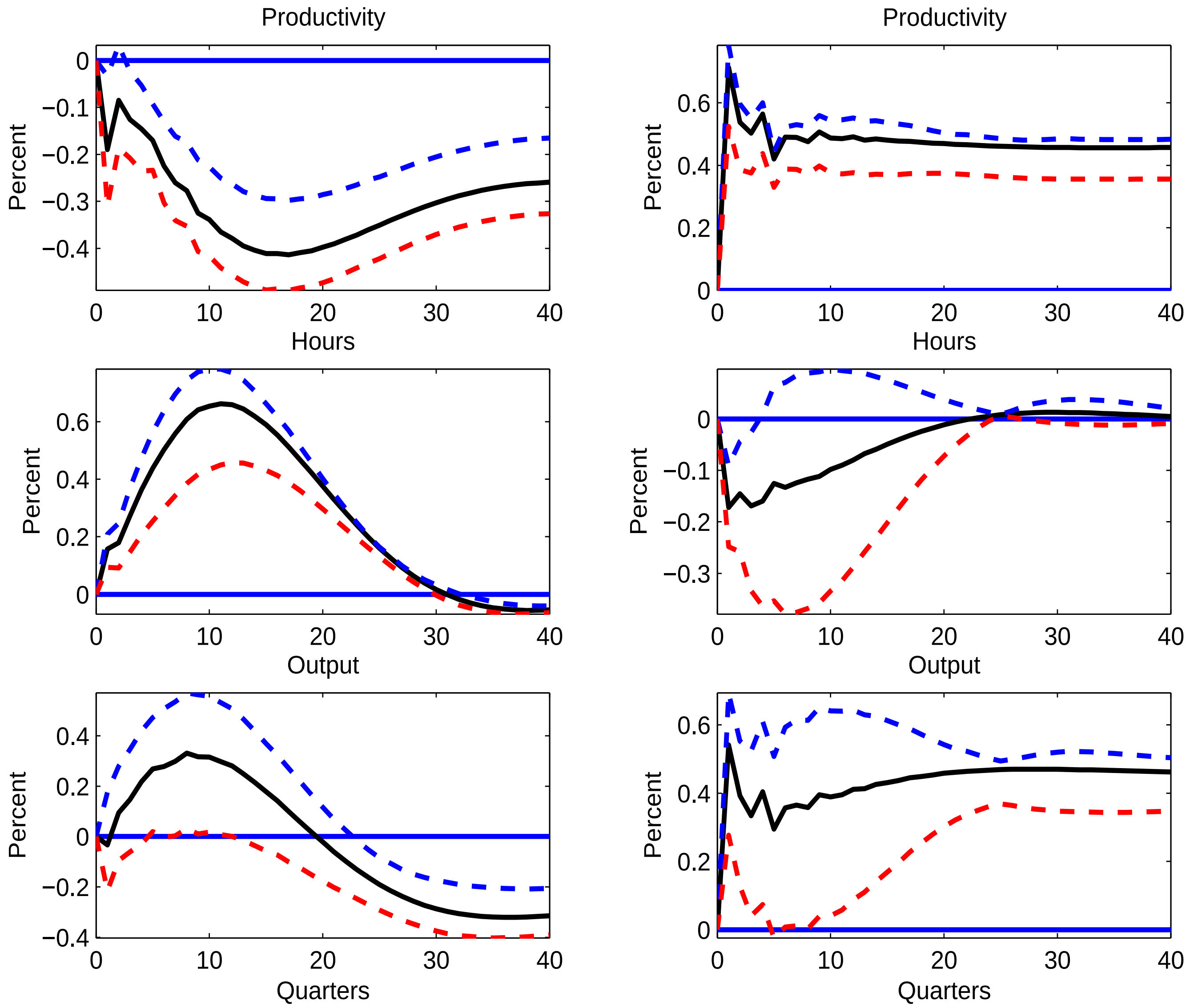

Figure 11: UK: whole economy, 4 lags in VAR, level-hours, long-run restrictions, ICT deflator, **investment-specific technology shock** (left column), **neutral technology shock** (right column)

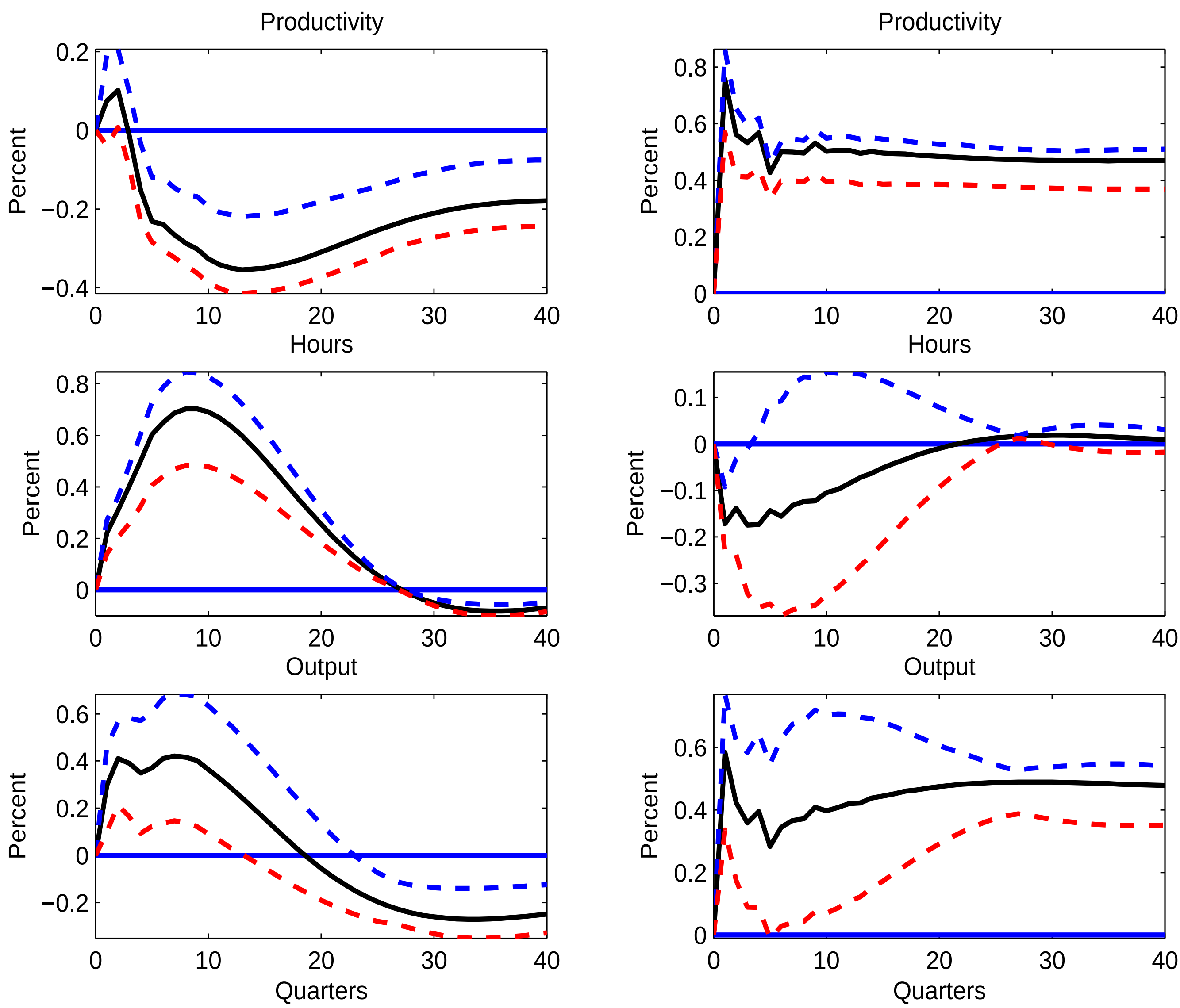

Figure 12: UK: whole economy, 4 lags in VAR, level-hours, long-run restrictions, **investment-specific technology shock** (left column), **neutral technology shock** (right column)—business investment deflator

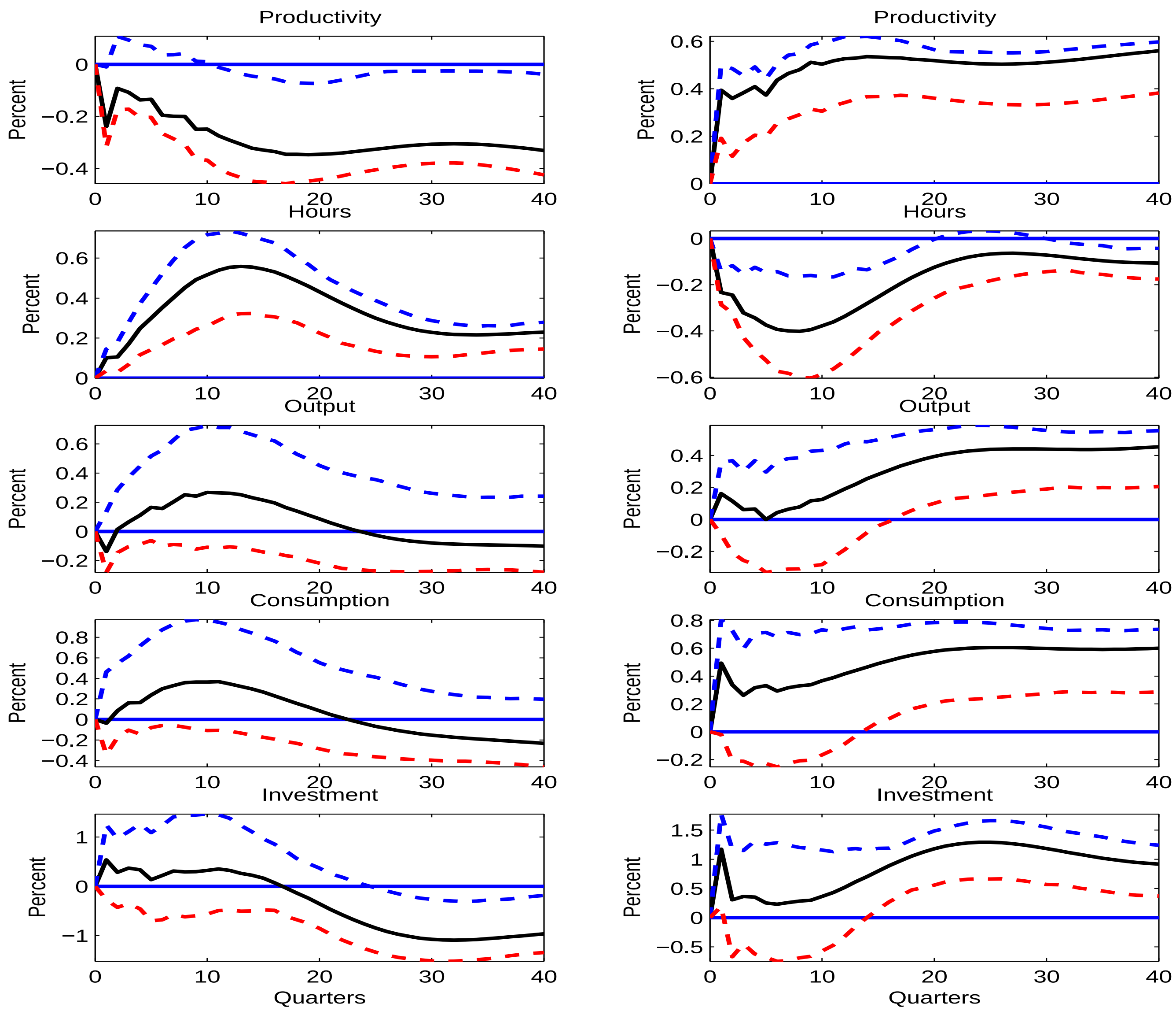

Figure 13: UK: whole economy, 4 lags in VAR, level-hours, long-run restrictions, ICT deflator. **Bias in responses**: with (solid) or without (dotted) a break in I/Y ratio

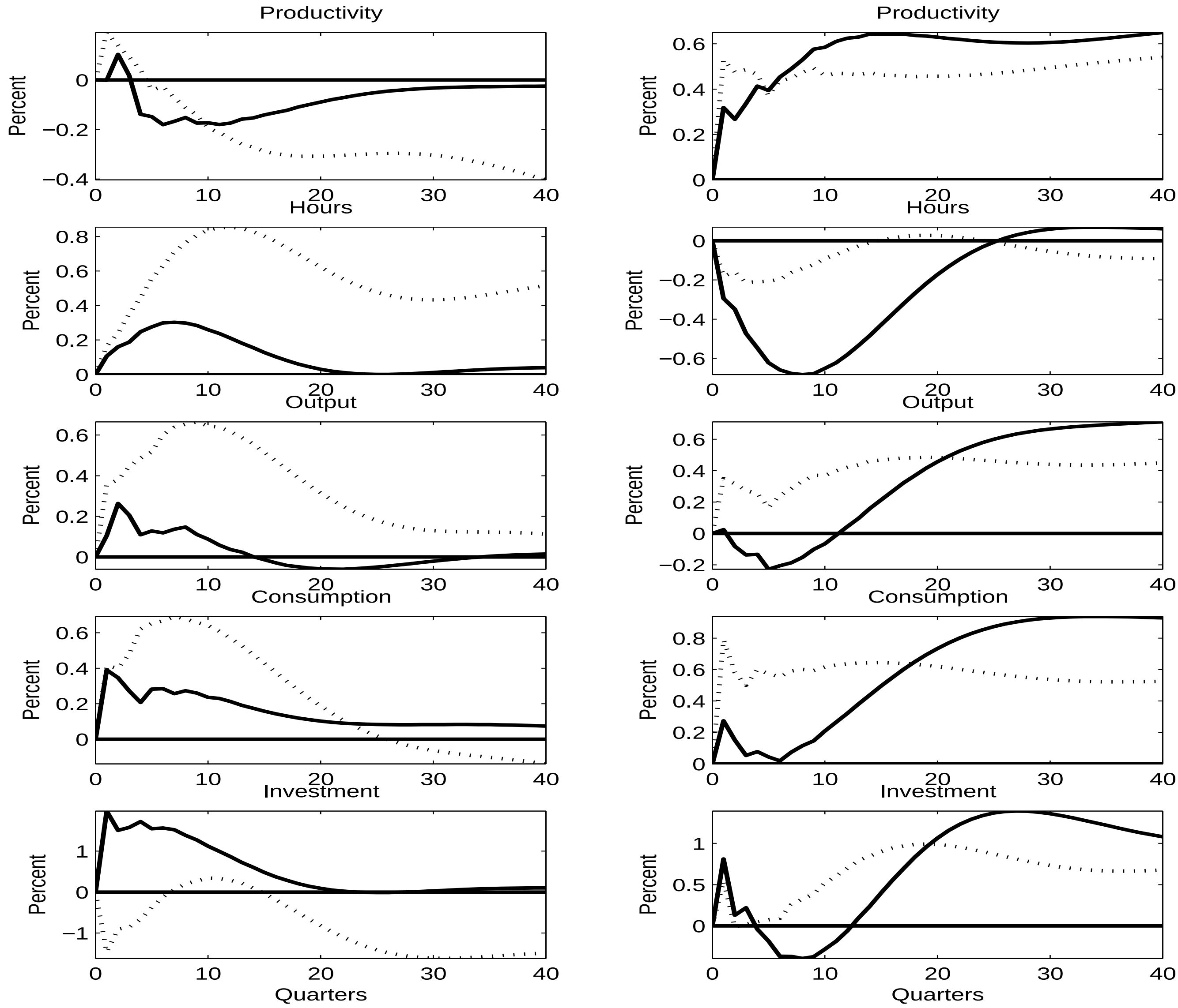

Figure 14: UK: whole economy, 4 lags in VAR, level-hours, long-run restrictions, business investment deflator, with break in I/Y ratio, **investment-specific technology shock** (left column), **neutral technology shock** (right column)

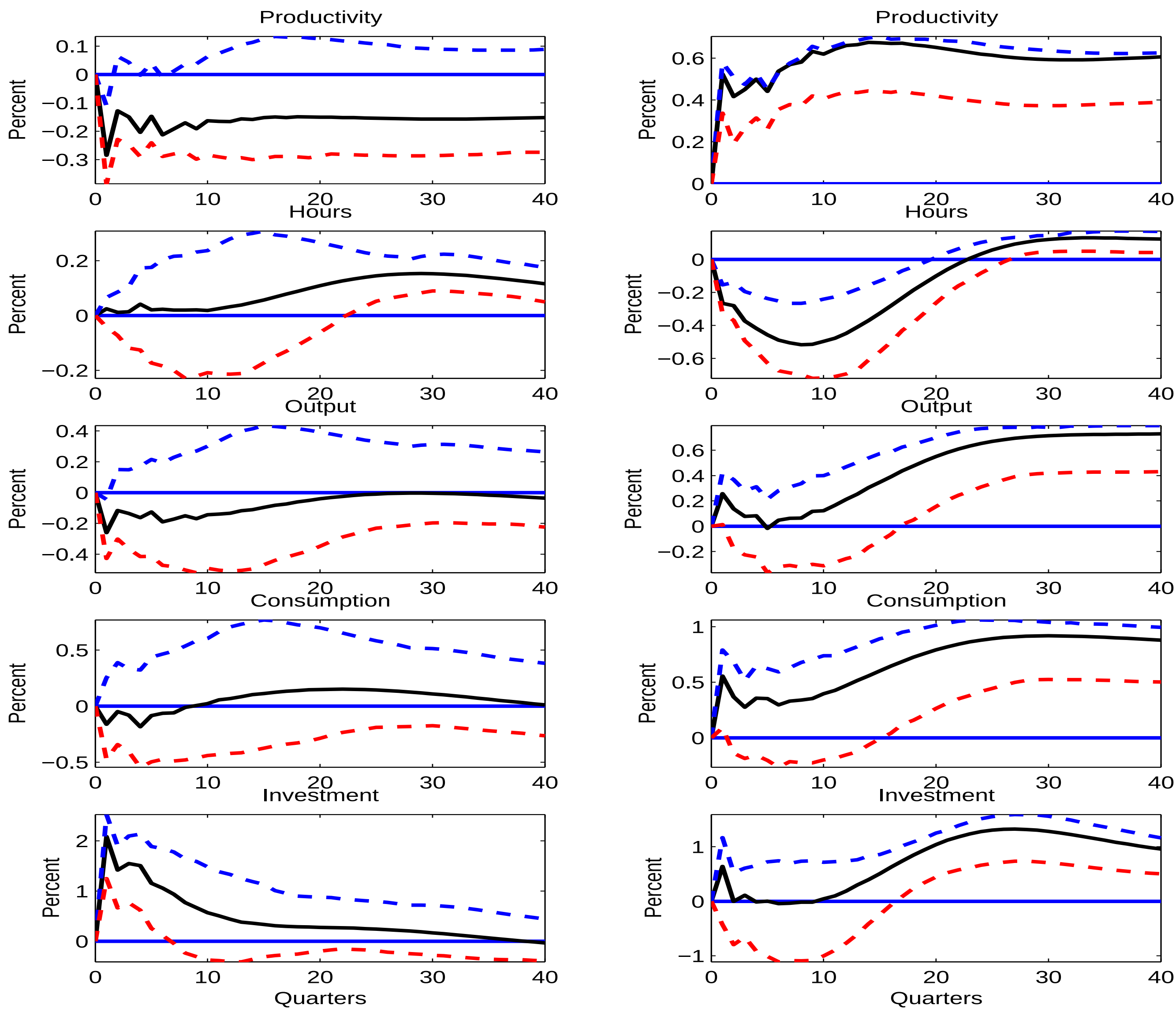

Figure 15: UK: whole economy, 4 lags in VAR, level-hours, long-run restrictions, ICT investment deflator, with break in I/Y ratio, **investment-specific technology shock** (left column), **neutral technology shock** (right column)

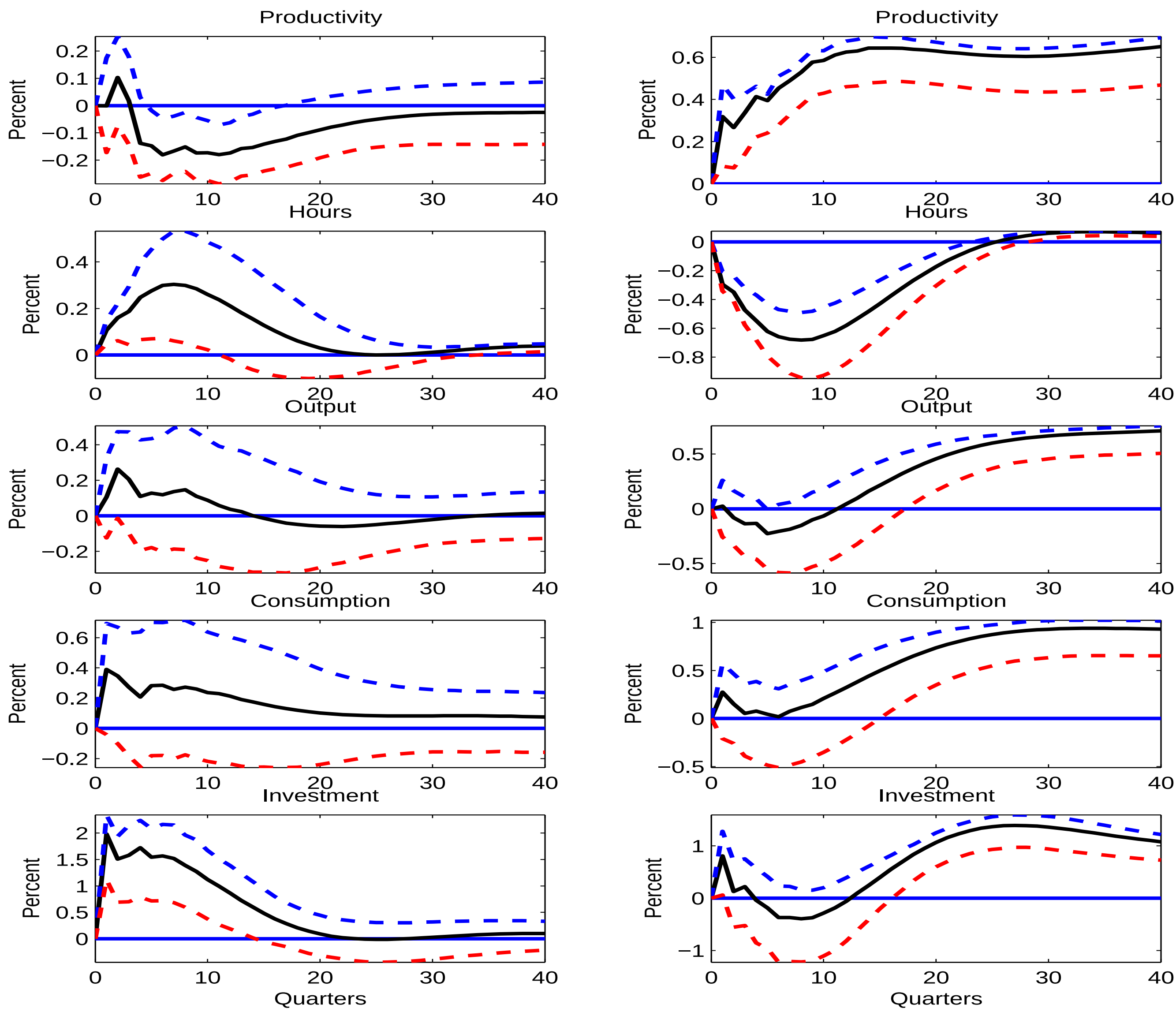

Figure 16: open economy specification (with real exchange rate): 4 lags in VAR, level-hours, long-run restrictions, with break in I/Y ratio

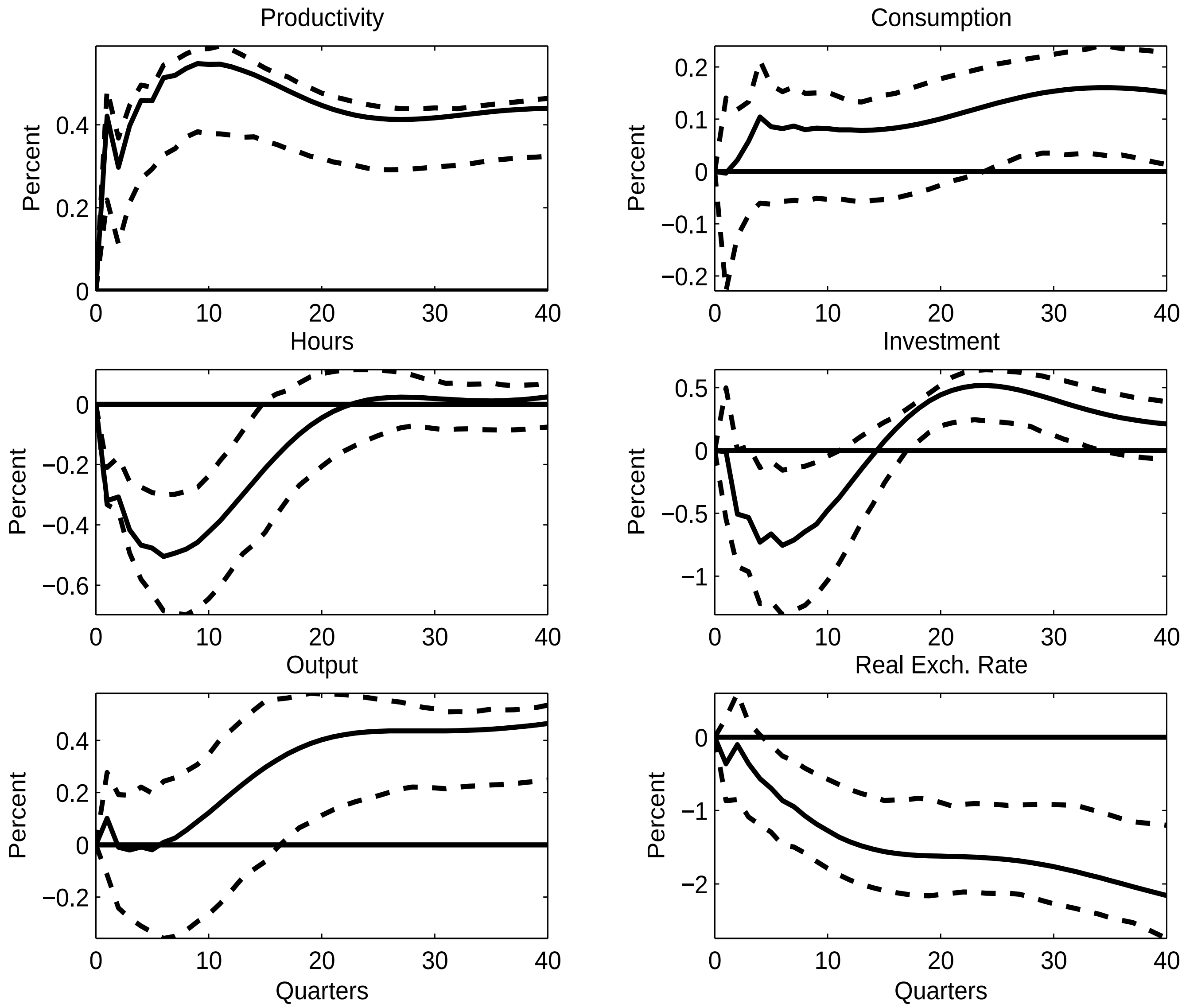

Figure 17: open economy specification (net exports): 4 lags in VAR, level-hours, long-run restrictions, with break in I/Y ratio