The Source of Historical Economic Fluctuations: An Analysis using Long-Run Restrictions

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Abstract

This paper investigates the source of historical fluctuations in annual US and UK data extending back to the 19th century. Long-run identifying restrictions are used to decompose shocks into technology shocks and other shocks. For the US data, a variety of models with differing auxiliary assumptions are investigated. In the US, the impact of technology shocks on labor input in the pre-WWII period is the opposite of its impact in the post-WWII period in most models. The UK data shows more sample stability, with the short-run impact of technology on labor being negative. The decomposition also reveals important changes in the volatility of shocks over time.

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I. Introduction

There has been a recent surge in the number of papers studying real business cycles and the role that technology shocks plays in generating cyclical movements in macroeconomic data. Such renewed interest in technology-driven business cycles has been fueled by the finding of recent empirical studies that labor input falls, at least in the short run, in response to a positive technology shock – see Shea (1998), Galí (1999), Basu, Fernald and Kimball (1999) and Francis and Ramey (2002). These results have generated a good deal of discussion because they raise fundamental questions about the empirical relevance of the technology-driven real business cycle hypothesis.

The goal of this paper is to analyze the historical role played by technology shocks in the US and the UK by studying the fluctuations in data extending back to the 19th century. Our approach is to identify technology shocks using long-run restrictions as in Blanchard and Quah (1989) and Galí (1999). It seems particularly appropriate to use long-run restrictions for identification in truly long-run data. We carry out our analysis for the entire sample period and for two subsamples of the data, the pre- and post-WWII eras. Our subsample results are then compared to see if there have been any changes in the nature of technology shocks or in their transmission mechanism. To check the robustness of our results, we identify technology shocks using various assumptions about the source of nonstationarity in the data. The time series properties of the data is a concern at the heart of the debate between those who uncovered this new labor input response to technology and those skeptics who still believe in the traditional RBC paradigm.[1]

[1] Several economists have expressed concern that this new finding could be a direct result of the stationarity assumptions made of the time series used in the structural vector autoregressions; see Christaino, Eichenbaum and Vifusson (2003).

We find that some results differ depending on the assumptions made about the time series process driving hours. We perform three cross-checks on the results of the different specifications and conclude that the unit root assumption gives the most reasonable results. In both the unit root and linear trend specifications, the impact of technology shocks on labor input in the pre-WWII period is the opposite of its impact in the post-WWII period in US data. The UK data shows more sample stability, with the short-run impact of technology on labor being negative in most cases. For both countries, we also find important changes in the volatility of shocks over time.

The remainder of the paper is organized as follows: Section II presents an overview of the historical US data. The econometric methodology and the responses to a technology shock in a Structural Vector Autoregressions (SVAR) are presented in Section III. There we examine the responses for a bivariate system of productivity and labor input under varying assumptions about the trend in hours. We subject the results to three heuristic tests to determine which system is the most valid. Section IV explores the effects on other variables such as consumption and investment, and highlights the features of the shocks identified by this approach. Section V examines the historical responses for the United Kingdom to check whether our findings are unique to the United States. Concluding remarks are offered in Section VI.

II. Overview of the US Historical Data

In this section we present an overview of the US data as a preliminary step to estimation of the structural VAR. We use annual data for the US for the time period 1889 - 2002. The principle variables studied are labor productivity and hours for the private business sector. In augmented models and in additional tests, we also use data on consumption, investment, government spending, the price level and money. All series except productivity and prices are divided by the total population age 16 and older to put them on a per capita basis.

Data for the early part of the sample come from John W. Kendrick's *Productivity Trends in the United States* (1961), *Historical Statistics,* Balke and Gordon (1989), and Anderson (2002). Data for the later part of the sample are obtained from the Bureau of Labor Statistics (BLS), the BEA, the *Economic Report of the President*, and the Federal Reserve. The appendix provides a detailed description of all the data and their sources.

Figure 1 plots output per hour and hours per capita (measured relative to the population age 16 and older), both in log levels and as deviations from a linear trend. It is difficult to distinguish the cyclical movements in output per hour because the overall upward trend is so strong. The bottom left graph makes the higher frequency fluctuations more evident by plotting deviations relative to a linear trend. It is clear that the movements around trend are quite persistent.

Hours per capita fall by 37 percent from 1889 to 2002. The fall is not uniform, however. Hours per capita display only a slight downward trend from 1889 to 1929, followed by a substantial drop in the 1930s, a partial recovery during WWII, and a continuing downward movement in the 1950s through 1970s. Beginning in the 1980s, hours per capita start rising again. As the bottom right graph shows, the deviations of hours per capita from a linear trend are also quite persistent. The data appendix discusses how the private business sector productivity and hours relate to other aggregates, such as the nonfarm sector and total GDP.

We performed standard unit root tests in order to study some of the stationarity properties of the series. Table 1 shows the results of statistical tests of the null hypothesis of a unit root against alternatives with a linear deterministic trend or a quadratic trend. Panel A shows results for the entire sample, Panel B shows results for the pre-WWII period, and Panel C shows results for the post-WWII period. Because the subsamples have a small number of observations, the results of the unit root tests should be viewed with some caution.

A unit root cannot be rejected at any reasonable significance level for any variable when the full sample is used. On the other hand, there is evidence against a unit root in two cases in the subsamples. In the prewar sample from 1889-1939, the p-value for the test of the hypothesis of a unit root in hours versus a quadratic trend is 0.005. Thus, a quadratic trend describes the behavior of hours relatively well in the early period. In the postwar period, there is evidence against a unit root in favor of a linear trend in the case of output.[2]

The only unit root required for our identification scheme is a unit root in labor productivity. For all samples, the p-value is quite high so a unit root cannot be rejected at conventional significance levels. On the other hand, the tests on hours give varying results. Since the results from the VAR can be sensitive to some of the maintained hypotheses about stationarity of the labor series, we will show results from systems with varying assumptions about trends in hours per capita.

[2] The log of output is simply the sum of the log of output per hour and the log of hours.

III. Estimated Responses to a Technology Shock

A. Econometric Methodology

Our baseline specification is a bivariate model of labor productivity and labor input similar to the benchmark models of Galí (1999) and Francis and Ramey (2002). Under this specification technology is identified as the only shock that can have permanent effects on labor productivity. This assumption is less restrictive than Blanchard and Quah's (1989) identification assumption since it allows non-technology shocks, such as changes in government spending, to have permanent effects on output. On the other hand, if changes in distortionary taxes affect the capital-output ratio, and hence labor productivity, this identification scheme classifies them as technology shocks. For example, a cut in capital tax rates that permanently raised labor productivity would be called a "technology shock" in our model.

Consider the system:

$$\begin{bmatrix} \Delta x_t \\ \Delta n_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^m \end{bmatrix}$$

x_t denotes the log of labor productivity, n_t denotes the log of labor input, ε^z denotes the technology shock, and ε^m denotes the non-technology shock. C(L) is a polynomial in the lag operator. We maintain the usual assumption that ε^z and ε^m are orthogonal. Our assumption identifying the technology shock implies that $C^{12}(1) = 0$, which restricts the unit root in productivity to originate solely in the technology shock.

Another way to think about this restriction is through the estimation method suggested by Shapiro and Watson (1988). Consider the following system of equations:

(1a) $$\Delta x_t = \sum_{j=1}^{p} \beta_{xx,j} \Delta x_{t-j} + \sum_{j=0}^{p-1} \beta_{xn,j} \Delta^2 n_{t-j} + \varepsilon_t^z .$$

(1b) $$\Delta n_t = \sum_{j=1}^{p} \beta_{nn,j} \Delta n_{t-j} + \sum_{j=1}^{p} \beta_{nx,j} \Delta x_{t-j} + \theta \varepsilon_t^z + \varepsilon_t^m .$$

As discussed by Shapiro and Watson (1988), imposing the long-run restriction is equivalent to restricting the other variables to enter the equation in double-differences. Because the current value of $\Delta^2 n_t$ will be correlated with ε_t^z in the first equation, instrumental variables must be used to estimate the equation. Using lags one through p of Δx_t and Δn_t as instruments for the first equation yields estimates that are identical to those obtained using matrix methods.

The second shock to the system, ε_t^m , is identified by including the estimated residual from the first equation in the second equation, along with the standard lags of the variables, as shown in equation (1b). The estimated residual from this equation, ε_t^m , is identified as the "nontechnology" shock. This specification incorporates our baseline assumption of a unit root in hours. We also estimate specifications with deterministically-detrended level of hours. Christiano, Eichenbaum, and Vigfusson (2003) (CEV) have argued for the specification that assumes stationary hours or a linear trend in hours per capita in the post-WWII data.

B. Bivariate First-Differenced Labor Results

We first consider the results from the bivariate model of productivity and hours under the assumption of a unit root in hours. We use two years of lags in the specifications. The results for the full sample and the two subsamples are presented in Figures 2 and 3. Figure 2A shows the responses of productivity and labor input to a shock to technology for the full sample. Both productivity and labor respond positively, and persistently so, to the technology shock over the entire sample period. In Figure 2B we include a dummy variable for World War II and, except for a slight change in magnitude, the results are unchanged.

We check for subsample stability of our results by splitting the sample period and looking at the impulse responses pre- and post-WWII. We should caution that the subsamples each contain less than 60 annual observations. Figure 3A shows the pre-WWII impulse responses to the identified technology shock. Again, except for magnitude changes, the results are the same as those found for the full sample; productivity and labor respond positively to the technology shock with no indication of returning to their pre-shock levels. However, as shown in Figure 3B, the post-WWII responses are qualitatively different from the previous sets of results. Productivity still rises in response to a technology shock but the shape of the impulse response is different from its previous counterparts. That is, instead of initially overshooting its new steady state as before, productivity gradually rises to its new steady state. The labor input response is also dramatically different from its earlier impulses: labor input falls in response to the technology shock. This result for the postwar period coincides with the findings of Shapiro and Watson (1988), Blanchard and Quah (1989), Galí (1999), Basu, Fernald and Kimball (1999) and Francis and Ramey (2002).

Interestingly, the negative response of labor to a positive technology shock appears to be a feature of only the post-WWII era.[3]

C. Detrended Labor Results

We now present results from specifications that make different assumptions about the process driving hours. The data generating process of labor has been a point of concern in the debates surrounding this new finding for technology-driven labor input. Shapiro and Watson (1988) and Galí (1999) found a negative response of total hours to technology shocks whether they assumed a unit root or a linear trend in total hours. Christiano, Eichenbaum, and Vigfusson (2003), however, argue that with hours *per capita* data they find a positive effect of technology on hours if they assume either stationarity or a linear trend. Recall from the unit root tests in Section II that we could not reject a unit root against the alternative of a linear trend, but could do so for private hours against a quadratic trend in the early subsample.

Under the assumption of a deterministic trend rather than a unit root, the system is modified as follows:

$$\text{(2a)} \qquad \Delta x_t = \sum_{j=1}^{p} \beta_{xx,j} \Delta x_{t-j} + \sum_{j=0}^{p-1} \beta_{xn,j} \Delta n'_{t-j} + \varepsilon_t^z \,.$$

$$\text{(2b)} \qquad n'_t = \sum_{j=1}^{p} \beta_{nn,j} n'_{t-j} + \sum_{j=1}^{p} \beta_{nx,j} \Delta x_{t-j} + \theta \varepsilon_t^z + \varepsilon_t^m \,.$$

[3] Galí, Lopez-Salido, and Vallés (forthcoming) find evidence of a weakening of the negative response of labor in the post-1982 period, which they attribute to changes in monetary policy.

where n_t' is detrended labor. The instruments used for the first equation are lags 1 to p of Δx and n'.

CEV argue that this type of specification is more general because it allows for a unit root in hours if it is there. This argument, which makes sense when long-run restrictions are not required for identification (such as monetary VARs with the federal funds rate), would not appear to apply in this case. Because the technology shock and non-technology shocks are identified correctly *only* if sufficiently stringent long-run restrictions are imposed, implementing weaker restrictions will lead to contaminated shocks. If hours have a unit root, the restrictions imposed in equation (2a) are insufficient for identifying the technology shock.

We first consider the results from a model in which hours have a linear trend. The results are presented in Figure 4. Panel A shows the responses for the entire sample, Panel B for the prewar period, and Panel C for the postwar period. For the entire sample, a positive technology shock raises productivity permanently, but leads to a drop in hours that takes a long time to wear off. The same pattern shows up for the prewar period in Panel B. In contrast, the post-WWII period shows that a positive productivity shock raises hours. Thus, the linear trend gives the exact *opposite* results from the first-difference specification *in every sample*.

Consider now the results obtained under the assumption that hours have a deterministic quadratic trend. These results are shown in Figure 5. For the entire sample in Panel A, productivity initially overshoots before converging to a higher steady state. Hours fall as a result of the positive productivity shock, and very slowly converge back to their previous value. The quadratic trend results for the prewar sample are shown in Panel B. Productivity shows the same pattern as for the entire sample. On the other hand, labor input responds negatively on impact but quickly returns to its original steady state approximately two years after the shock. In the postwar data, displayed in Panel C, productivity is again positive on impact and reaches its new steady state within four years after the initial shock. Hours in the postwar period also decline on impact. In the second year, though, the response becomes positive and stays positive for some time.

It is clear that the different detrending methods yield different results for the response of hours. To determine how much of the difference is from imposing the double-difference constraint in equation (1a) and how much is from the other specification differences, we estimate the following hybrid model.

(3a) $$\Delta x_t = \lambda_1 T + \lambda_2 T^2 + \sum_{j=1}^{p} \beta_{xx,j} \Delta x_{t-j} + \sum_{j=0}^{p-1} \beta_{xn,j} \Delta^2 n_{t-j} + \varepsilon_t^z .$$

(3b) $$n_t = \delta_1 T + \delta_2 T^2 + \sum_{j=1}^{p+1} \beta_{nn,j} n_{t-j} + \sum_{j=1}^{p} \beta_{nx,j} \Delta x_{t-j} + \theta \varepsilon_t^z + \varepsilon_t^m .$$

There are three differences between this equation system and the unit root system in equations (1a) and (1b). First, in this system there are quadratic time trend in both equations. Second, labor enters in log levels in the second equation. Note that the lag length is extended to p+1 so that the specification nests our unit root specification. The third difference, not shown in the equation, is the use of log levels of labor, lags 1 to p+1, and the time trends as instruments in the first equation. Thus, except for the long-run restriction imposed by the double-difference of labor in the first equation, the system nests all of the other specifications.

Figure 6 shows the results from this specification. Consider first results from the entire sample, shown in Panel A. Productivity behaves very similarly to the first-difference specification (Figure 2A), but the positive impact on labor in the hybrid specification does not appear to be permanent. The results are similar for the prewar period. The positive impact of the technology shock on labor is even less persistent in this case. For the postwar period, the impact on labor is still strongly negative, but in this case there is some movement above zero at year three.

D. Which Specification is Most Valid?

Table 2 summarizes the results for labor across the four different specifications. The results vary widely according to the sample period and the trend assumptions. If one took the unit root tests at face value and concluded that a quadratic trend should be used for the early sample and a unit root should be used for the late sample, one would then conclude that the short-run impact of a positive technology shock on hours is negative in both periods.

Given the small sample problems with the formal statistical tests, though, it would be useful to have other ways to determine which model produces the results that make the most sense. We therefore consider three heuristic methods for cross-checking the results: (1) Do nontechnology shocks have only transitory effects on the productivity, as implied by the identification scheme? (2) Do the estimated technology shocks follow "reasonable" historical patterns? (3) Are the technology shocks predictable by nontechnology events?[4]

[4] We also tried unsuccessfully to use a fourth cross-check: Are the estimated technology shocks correlated with other measures of technology? Following work by Shea (1998), we gathered data on patent applications for the entire sample to see whether there was any link between the technology shocks and patent applications. To our chagrin, preliminary tests on whether patent applications had a positive effect on labor productivity itself were negative. That

1. Do nontechnology shocks have only transitory effects on the productivity?

Figure 7 shows the results from all four models of the effects of a nontechnology shock on labor productivity and hours. Consider first the effects on productivity. Both the unit root and hybrid models imply that the nontechnology shock has a very transitory effect on labor productivity. In contrast, the linear trend model implies persistent effects of a nontechnology shock on labor productivity in the prewar period and seemingly permanent effects of a nontechnology shock on labor productivity in the postwar period. The quadratic trend model produces results that are less persistent than the linear trend model. Thus, these results suggest that the linear trend model does not impose enough restrictions to identify the technology shock, particularly in the postwar period. This test favors the unit root and quadratic trend specifications over the linear trend specification.

Although the behavior of hours in response to the nontechnology shock does not serve as a check on the identification assumptions, the difference in responses across the models is nonetheless interesting. In the unit root model, a nontechnology shock leads to a permanent rise in hours. In contrast, the quadratic trend model and hybrid model produce hours effects that last three to five years. The linear trend model produces persistent, but apparently not permanent, effects on hours.

2. Do the estimated technology shocks follow "reasonable" historical patterns?

The differing assumptions about the source of nonstationarity in hours leads to different estimated technology shocks. Table 3 shows the correlation between the different estimated technology shocks.[5] The technology shocks from the unit root and linear trend models have the lowest

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is, the results from a variety of specifications, particularly in the prewar period, suggested a negative effect of patent applications on labor productivity.

[5] These shocks are estimated separately across the two samples.

correlation, about 0.4. The shock from the quadratic trend model has a relative high correlation with most of the other shocks, sometimes above 0.9.

Figure 8 shows the estimated technology shocks from the first three models. The shocks from the hybrid model look almost identical to those from the first-difference model, so we omit them for better graph clarity.

The shocks share several patterns in common over periods of history. For example, all three estimates imply that technology shocks were higher than average in the years after 1918. The unit root results imply that the shocks were consistently positive through the mid-1920s, whereas both trend specifications imply extremely high shocks from 1918 through 1921, followed by some negative ones in 1922 and 1923. Similarly, all three estimates imply higher than average technology shocks beginning in 1934, a severe negative shock in 1974, and a series of higher than average technology shocks in the second half of the 1990s.[6]

A key difference in the estimated shocks is the behavior during the Great Depression. The linear trend specification implies that the Great Depression was characterized by a series of three substantial positive technology shocks, followed by a negative shock in 1933. In contrast, the unit root specification implies the Great Depression was characterized by a series of four increasingly negative shocks beginning in 1930. The quadratic trend specification implies small positive and negative shocks in the first three years, followed by a negative shock in 1933. Since it would be hard to believe that the economy could do so badly in spite of large positive technology shocks,

[6] We omitted World War II from the sample when we split the prewar and postwar. If WWII data is added to the early sample, the impulse responses do not change much in any specification. All models produce estimates of positive technology shocks during most of the years of WWII.

this "reasonable historical pattern" check on the results favors the unit root specification over the other two, particularly over the linear trend specification.

3. Are the technology shocks predictable by nontechnology events?

As argued by Evans (1992), technology shocks should not be Granger-caused by nontechnology variables such as government spending and monetary variables (Granger (1969)). Evans cast doubt on the use of the Solow residual as a measure of technology shocks by showing that monetary variables and government spending Granger-caused the Solow residual. Thus, an additional means to test whether the identified shocks are really technology shocks is to test whether they are Granger-caused by these types of variables.

For each subperiod, we regressed the estimated technology shocks on two lags each of log per capita government spending, log per capita money, and the log of the price level. (See the data appendix for details on these variables.) We then tested whether these variables Granger-caused the technology shock. The results are reported in Table 4. The results are strongly in favor of the technology shock estimated with the unit root specification. In neither time period do these variables Granger-cause the technology shock as estimated by the unit root specification.[7] In contrast, the p-values are very low for the case of the linear trend specification, indicating that monetary and government variables Granger-cause the estimated technology shock produced by this specification. The estimated shock for the quadratic specification fails the test in the early period (i.e. monetary and government variables Granger-cause the shock), but passes the test in the late period. The hybrid model passes the test in both periods.

To summarize, all three tests cast doubt on the linear trend model. Its estimates imply too much persistence in the effects of nontechnology shocks on productivity, it behaves oddly during the Great Depression, and it does not pass the Evans-style Granger causality test. The quadratic trend model does well by most counts, except for on the Granger-causality test during the first period. The unit root specification and hybrid model results pass all three tests. This evidence leads us to put more weight on the results from the specification that imposes the double-difference constraint on labor in the productivity equation.

IV. Features of Technology

As the results of the last section favor the unit root results over either deterministic trend specification, we use the estimates from the unit root specification to explore the historical role of technology and nontechnology shocks in more detail.

We begin by adding consumption and investment to the model in order to study the responses of those variables to an estimated technology shock. We augment the first-difference model with personal consumption and investment keeping the same key identifying assumption as in the bivariate case – technology is the only shock having permanent effects on productivity.[8] Our aim is to impose enough restrictions to only identify the technology shock.[9] The results are presented in Figures 9A - 9C. For the full sample productivity and labor respond as in the bivariate case – both respond positively and persistently to a shock to technology. This implies that the output response is also positive over the entire sample period. Consumption and investment also respond positively to the technology shock. The pre-WWII responses are shown in Figure 9B and again,

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[7] If we create technology shocks including WWII in the early sample, there is still no evidence of Granger-causality.
[8] The output response is the sum of the productivity and labor input responses.

except for differences in magnitude, the results are the same as found for the full sample. Finally, the post-WWII responses, presented in Figure 9C, are again qualitatively different from the full sample and prewar responses. Productivity approaches its steady state from below, instead of overshooting it as in the full sample and pre-WWII sample. Investment initially falls, albeit only minimally, before converging to its new steady state 6 periods after the initial shock. The labor input responds negatively on impact and stays below its previous steady state value for the duration of the impulse response period. The initial fall in labor input is enough to cause output to be negative, though insignificant, on impact.[10]

Why the response of labor differs so much across the two samples is not clear. Further research is needed, perhaps using higher frequency data, to determine whether the difference is due to changes in the structure of the private economy or perhaps is due to changes in monetary policy.

We now study the pattern of the two types of estimated shocks in more detail. Figure 10 shows the historical pattern of technology shocks and nontechnology shocks.[11] Figure 10A plots the technology series against the recession dates as identified by the National Bureau of Economic Research (NBER). The technology series tend to decline around these recessions dates. Close examination of the graph reveals that recessions are usually associated with technological regress

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[9] Francis and Ramey (2001) shows how other identifying assumptions can be incorporated into a larger model of this nature to identify other 'structural' shocks.

[10] The results from the SVARs imposing cointegration between consumption and investments are qualitatively the same as those presented in Figures 9. To save space we do not present these results in the text but these results are available upon request to the interested readers.

[11] We show the shocks estimated separately for each subperiod. The correlation between the technology shocks estimated using the entire sample from 1889 and the shock estimate using 1889-1939 data is 0.966. Thus, adding the sample from 1940-2002 does not change the estimated prewar shocks much. On the other hand, the correlation of the technology shocks using the entire sample and those estimated using the sample from 1947-2002 is 0.48, so the sample period used does affect the estimation of the post-WWII shocks.

while the same cannot be said for peak dates. That is, peak dates do not coincide with upward spikes in technology.

The four years with the most negative technology shocks are 1908, 1914, 1930, and 1932. It is interesting to note that all four of those dates are associated with problems in the financial system. A banking panic occurred in October 1907. 1914 marked the outbreak of WWI, which brought some financial difficulties. For example, the New York Stock Exchange had to be closed for a day (Friedman and Schwartz (1963)). Finally, the banking crises of the early 1930s are well-researched. During the post-WWII period, the four years with the most negative shocks are 1955, 1959, 1974, and 1987. 1955 was the end of the auto investment boom, but it is not clear why that would be a negative technology shock. 1959 is associated with the steel strike, 1974 with the first oil crisis and the collapse of the exchange rate system, and 1987 with the stock market crash. (See Eckstein and Sinai (1986) for a chronology of the post-war events.) It is not clear, though, that there was a link between these events and the estimated shocks.

On the positive side, the estimates suggest that the period from the late teens to the mid 1920s was characterized by a string of positive technology shocks. Also interesting is the series of high estimated positive technology shocks in the second half of the 1930s. Why was output growth so slow during this period if technology shocks were so positive? One possible explanation might be found in Cole and Ohanian (2003). They argue that slow growth persisted after the Great Depression because New Deal policies led to cartelization. According to their story, these policies led to a significant rise in real wages despite the low growth of output and employment. If cartel behavior in the labor market led to artificially high real wages, firms would have cut back hours in order to raise productivity to equal to the real wage. According to our decomposition, this event is counted as a shock that has a permanent effect on labor productivity.

The four most negative nontechnology shocks occur in 1919, 1921, 1932 and 1938. According to the estimates, there was also a series of negative nontechnology shocks during the Great Depression. Thus, according to these estimates the Great Depression can be attributed to adverse events in both types of shocks. During the postwar period, the four most negative nontechnology shocks occurred in 1954, 1958, 1974, and 1982. It is interesting that three of four of these instances occurred one year before the biggest negative technology shocks of the period.[12]

Finally, a glaring feature of both the technology and nontechnology shocks in Figure 10 is that both series appear to have become less volatile in the postwar era.[13] We carry out an F-test of equal variance between the variances of the prewar and postwar technology shocks. Given the variance of the prewar technology of 15.60 with sample size 48, and similar figures for the postwar technology of 1.80 and 53 respectively, the value of the F-statistic is 8.67 (15.60 ÷ 1.80). We compare this to a critical F-value with 47 numerator degrees of freedom and 53 denominator degrees of freedom. We reject the null of equal variance for all conventional values of the F-statistics which implies that the postwar technology is indeed (significantly) less volatile than the prewar technology.

[12] We checked to see whether the nontechnology shocks Granger-caused the technology shock, but there was no evidence that they did.

[13] The reduced volatility of the postwar recessions have been documented by Zarnowitz and Moore (1986), Taylor (1986), and DeLong and Summers (1986) all appearing in Robert J. Gordon's NBER symposium; *The American Business Cycle: Continuity and Change,* published by the Chicago Press. More recently papers such as McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Stock and Watson (2002) have documented a decline in output volatility post 1984.

The results are similar for the nontechnology shock, whose variance falls from 14.5 in the prewar period to 3.3 in the postwar period. An F-test of equal variance yields an F-statistic of 4.39. With the same sample sizes as above we reject the null of equal variances of the nontechnology shock at all conventional levels of significance. Thus, according to these estimates both types of shocks became significantly less volatile in the postwar period.

V. Results for the United Kingdom

We now consider estimates for the United Kingdom from 1855 to 2001. Figure 11 plots the basic series. Because of data availability, employment is used rather than hours.[14] Output per worker shows a strong upward trend, with a noticeable dip beginning in 1919. Over the span from 1855 to 2001, employment per capita displays some low frequency movements, but no overall trend downward like the US hours per capita series.

We estimated the benchmark bivariate model with a unit root in labor productivity and labor input for the UK. Again we estimate using the full sample 1855 – 2001, and for the pre- and post-WWII subsamples. The impulse responses are presented in Figure 12.

The full sample impulse response for productivity is similar to its full sample counterpart for the US, see Figures 2A and 2B. Productivity overshoots before converging to a higher steady state value. The shape of the labor response is also similar to its US counterpart; however, the initial response is negative for the UK. Again the prewar responses are similar to the full sample responses except for minor differences in the magnitudes of the responses. Labor again responds negatively on impact. In the postwar period, productivity displays a more hump-shaped pattern.

The labor input response is more negative on impact, and never becomes positive. Overall, though, the UK data does not suggest the dramatic changes across subperiods that the US data indicates.

The impulse responses for the UK have the feature that labor responds negatively to a technology shock, at least in the short run. Therefore, results for the UK confirm the findings of Galí (1999) and Francis and Ramey (2002) regardless of the time period studied. In this sense the UK impulse responses are different from the impulse responses of the US.[15]

The estimates of the shocks are shown in Figure 13 - the shaded areas represent the pre- and post-war business cycle dates for the UK. We show the shocks estimated using the entire sample since there was less evidence of subsample instability. The largest negative technology shocks, Figure 13A, were in 1880, 1919, 1920, and 1926, whereas the largest negative nontechnology shocks, Figure 13B, were in 1879, 1884, 1908, and 1921. Finally, an interesting feature of these plots is that the nontechnology shock does a good job of picking up the recession dates. That is, invariably the recession dates coincide with dips in the nontechnology shocks. Galí (1999) had a similar finding for his US postwar nontechnology shock.

Table 5 shows the variance of each type of shock for four subsamples: the pre-WWII period from 1858-1938, the post-WWII period from 1950-2001, the pre-WWI period from 1858-1913, and the interwar period from 1918-1938. The fall in variance of the technology shock is not as

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[14] The appendix gives details about the data.

[15] Here is brief summary of results from alternative specifications. The only case in which one can reject a unit root is for hours in favor of a linear trend in the early sample only. The linear trend structural VAR model gives results similar to the US: positive effects of technology on labor in the full sample and the post-war sample, negative effect

pronounced as in the US (a 90 percent fall for the US versus 64 percent for the UK), whereas the fall in the nontechnology shock is about the same (about 75 percent). The era of the highest volatility is the interwar period, 1918-1938. The variances of both the technology and nontechnology shocks during this period are six times higher than their variances in the post-WWII period.

Are the shocks correlated across countries? For the overlapping periods, 1892-1938 and 1950-2001, the correlation of the estimated technology shocks is around 0, equal to –0.05.[16] The nontechnology shocks show more signs of correlations across countries, with a correlation of 0.437.

VI. Conclusions

This paper has presented estimates of models with long-run restrictions on historical US and UK data in order to study the nature and consequences of the shocks moving labor productivity, hours, and output. Following Galí (1999), we identify the technology shock to be the only shock that can have a permanent effect on labor productivity.

For US annual data from 1889-2002, we estimated the model under a variety of assumptions about the nature of the nonstationarity in hours. We compared results from models that assumed a unit root in hours, a linear trend, a quadratic trend, and a hybrid model. Cross-checks on the results, such as Granger-causality tests on the shocks, led us to conclude that the unit root specification led to the most reasonable results. According to this specification, a positive technology shock leads

on labor in the early sample. In the quadratic model, labor is negative for 2 years then positive in the full sample; negative in the early sample, and positive in the late sample.

[16] The finding that technology shocks are uncorrelated across the US and UK is consistent with Costello (1993).

labor to rise in the period from 1889-1939. In contrast, the same type of shock leads labor to fall in the period from 1947-2002.

We also investigated some of the characteristics of the shocks. We found that the volatility of both types of shocks, technology and nontechnology, fell dramatically in the post-WWII period in the US. We also found that both types of shocks had very negative realizations during the Great Depression.

The last part of the paper analyzed UK data from 1855 to 2001. For the UK, positive technology shocks had a negative short-run impact on labor in every subsample. We also found that the volatility of both types of shocks hitting the economy during the interwar period was particularly high. While there was some correlation of the nontechnology shocks across countries, there was no evidence of correlation of the technology shocks across countries.

We feel that this paper has studied only a few facets of the interesting features of the shocks identified using long-run restrictions. Further research in the area should try to augment the data to determine how the estimated shocks are correlated with other observable variables on technology and nontechnology shocks.

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Data Appendix

US Data

Total Population age 16 and over:

Data Sources: 1889-1938 data from *Historical Statistics*, Tables A-6 and A-29. 1939-2002 data from *Economic Report of the President, 2003*, Table B-34.

Series Creation: 1889-1899: Total resident population multiplied by ratio of resident population age 16+ in 1900 to resident population (all ages) in 1900. 1900-1938: Resident population age 16+ plus armed forces overseas during WWI. 1939-1999: Total population less population ages 0 – 15. 2000-2002: Total population multiplied by ratio of population 16+ in 1999 divided by total population in 1999.

Real GDP, GDP Deflator, Consumption, and Investment:

Data Sources: Real GNP and deflator 1889-1928 from Balke and Gordon, *Journal of Political Economy,* 1989. Real consumption expenditures and gross private investment 1889-1928: John Kendrick, *Productivity Trends in the United States*, 1961, Table A-IIa. Chain-weighted GDP, consumption and investment 1929-2002: BEA NIPA from www.bea.gov.

Series Creation: The pre-1928 data were multiplied by the ratio of the BEA data in 1929 to the historical data in 1929.

Productivity, Hours, and Output in Private Business and Nonfarm Private Business:

Data Sources: 1889-1946: John Kendrick, *Productivity Trends in the United States*, 1961, Tables A-X, A-XXII, A-XXIII. 1947-2002: BLS Productivity data from www.bls.gov.

Series Creation: 1889-1946 data were multiplied by the ratio of the BLS data in 1947 to the historical data in 1947.

Appendix Figure: For the purposes of the appendix figure only, we used information from NIPA data so that the output indexes could be converted to levels in order to compare across aggregates. We used NIPA data on business less housing for private business and business less housing less farm for private nonfarm business. Similarly, we used Kendrick hours totals for private business and nonfarm private business to rescale index series to levels.

Total Hours:

Data Sources: 1889-1947: John Kendrick, *Productivity Trends in the United States*, 1961, Tables A-X (total hours including military). 1948-2002: BLS and BEA NIPA Table 6.9 (Hours worked by full-time and part-time employees by sector).

Series Creation: We created series for 1948 – 2001 to match Kendrick's historical series. The BLS series gives an index of total hours worked in private business, including sole-proprietors and unpaid family workers but excluding general government and nonprofit institutions. On the other hand, the BEA series gives total hours worked by full-time and part-time employees by sector, but excludes sole proprietors. The lack of sole proprietors should not be important for creating a series on government worker hours. Thus, we used the BEA series on hours worked in government and multiplied it by the ratio of Kendrick's government hours to total hours in 1948 to create a government hours series that was consistent with Kendrick's and that gave the same ratio of government to total hours at the splice point. (We could not figure out why the two government hours series were so different at the splice point. In 1948, the Kendrick series was 10,887 whereas the BEA's series was 13,110. Because Kendrick constructed his private and government hours on a consistent basis, we decided to splice the various series from BLS and BEA to his series rather than the reverse.) We then multiplied the BLS private hours series by the ratio of Kendrick's private hours series to the BLS private hours series in 1948. Total hours are the sum of the spliced government series and the private hours series.

Money:

M2: For the period 1959-2002, we used M2 from the Board of Governors of the Federal Reserve. The earlier series are from Richard Anderson, "Some Tables of Historical US Currency and Monetary Aggregates Data," March 2002 manuscript. For 1947-1958, we use Rasche's M2 series. Because Anderson argues that Friedman and Schwartz M4 series is most comparable for the early period to M2 for the later period, we use M4 where possible, and otherwise M3.

Overview of the US Data

As discussed in the text, we focus on the private business sector. This appendix displays some of the raw data in order to show how private business differs from nonfarm private business and GDP. As discussed above, we had to construct a partial series on total hours to match up to GDP.

The Appendix Figure shows hours, output and productivity for three different aggregates: private business plus government (or total GDP), private business, and nonfarm private business. The three hours per capita measures have different movements. The most stable hours measure is the one for the nonfarm private business sector, a sector that has been the focus of some of the work done on post-WWII data. It is clear, though, that focussing on this narrower segment of the economy misses some key movements in total hours per capita over the last century. For example, the nonfarm hours series implies that hours worked per capita was the same in 2002 as it was in

1889, whereas the total hours series and private hours series show declines ranging between 31 and 45 percent (in log points). The drop would be even greater if hours worked in private households were included. According to Census statistics, in 1900, 5.4 percent of the civilian labor force worked in private households. In 2001, only 0.53 percent of the civilian labor force worked in private households.

All three output measures display similar growth rates, as seen in Panel B. Panel C shows productivity growth in the three sectors, using an index that takes the value of 100 in 1992. The total and private business indices display very similar patterns. On the other hand, the nonfarm private business sector shows steeper drops in productivity during the Great Depression, but faster growth overall.

We chose to focus our attention on the private business sector rather than nonfarm private business because the former is broader. Although total GDP is broader still, we do not use data for that sector because the hours data are not as comprehensive. As discussed above, we had to make a number of assumptions to construct the total hours series. Furthermore, the construction was only possible for annual data, so the results cannot be compared to results using postwar quarterly data.

UK Data

The historical data through 1959 are from C.H. Feinstein, *National Income, Expenditure and Output for the United Kingdom 1855-1965*.

The historical employment data are from Table 57, column (3). No splicing is done to take into account the fact that data from 1855 – 1919 includes Southern Ireland and the data from 1920-on does not because the population figures (which divide the employment figures) have the same feature. The employment data include the armed forces and self-employed.

The historical productivity data are from Table 20 of Feinstein. The population series used is for ages 16 to 64. Before 1900, population numbers for this age group was available only each decade. Total population was available annually, so we interpolated the ratio between the two between decades and multiplied total population by the ratio to obtain population age 16-64.

The more recent data on population were sent to us by the Population Unit of the ONS. The recent data on productivity and employment are from the web site: http://www.statistics.gov.uk/STATBASE.

Table 1: ADF Unit Root Tests
Private Business Sector
(Logarithms, per capita; lags chosen optimally up to max=4)

A. Full Sample, 1889-2002

	H_0: Unit root vs. H_a: Linear trend		H_0: Unit root vs. H_a: Quadratic trend	
Variable	**p-value**	**Lags included**	**p-value**	**Lags included**
Labor Productivity	0.760	4	0.971	4
Hours	0.526	3	0.360	3
Real Output	0.196	2	0.268	3

B. Pre-War Sample, 1889-1939

	H_0: Unit root vs. H_a: Linear trend		H_0: Unit root vs. H_a: Quadratic trend	
Variable	**p-value**	**Lags included**	**p-value**	**Lags included**
Labor Productivity	0.571	2	0.638	2
Hours	0.733	2	0.005	4
Real Output	0.389	2	0.151	2

C. Post-War Sample, 1947-2002

	H_0: Unit root vs. H_a: Linear trend		H_0: Unit root vs. H_a: Quadratic trend	
Variable	**p-value**	**Lags included**	**p-value**	**Lags included**
Labor Productivity	0.272	2	0.986	2
Hours	0.845	4	0.162	3
Real Output	0.029	2	0.161	2

Table 2
Effect of a Positive Technology Shock on Hours

	Entire Sample 1889-2002	Prewar Sample 1889-1939	Postwar Sample 1947-2002
Unit root	Permanent positive effect	Permanent positive effect	Temporary negative effect
Linear trend	Persistent negative effect	Persistent negative effect	Persistent positive effect
Quadratic trend	Mildly persistent negative impact	One year negative impact, then return to normal	One year negative impact, followed by several years of positive effects
Hybrid Model	Persistent positive effect	Persistent positive effect	Two year negative impact

Table 3
Correlation of Estimated Technology Shocks
(1892-1939 below the diagonal; 1950-2002 above the diagonal)

	Unit Root	Linear Trend	Quadratic Trend	Hybrid
Unit Root	1	0.405	0.890	0.936
Linear Trend	0.367	1	0.736	0.474
Quadratic Trend	0.658	0.906	1	0.854
Hybrid	0.954	0.514	0.780	1

Table 4: Granger Causality Tests
Dependent Variable: Identified Technology Shocks

Model	Prewar: 1892-1939		Postwar: 1950-2002	
	P-value on F-test	R-squared	P-value on F-test	R-squared
Unit root	0.531	0.112	0.648	0.084
Linear trend	0.000	0.541	0.041	0.239
Quadratic trend	0.000	0.430	0.267	0.145
Hybrid model	0.152	0.197	0.871	0.050

The tests are based on a regression of the technology shock on a constant and two lags each of log per capital government spending, log per capita money, and log GDP deflator. The null hypothesis is that all coefficents on these variables (excluding the constant) are zero.

Table 5: Variance of UK Shocks

Time Period	Technology Shocks	Nontechnology Shocks
1858 – 1938	5.63	5.23
1950 – 2001	2.04	1.34
1858 - 1913	3.45	4.43
1918 - 1938	12.20	8.13

Figure 1
US Labor Productivity and Hours in Private Business, 1889-2002

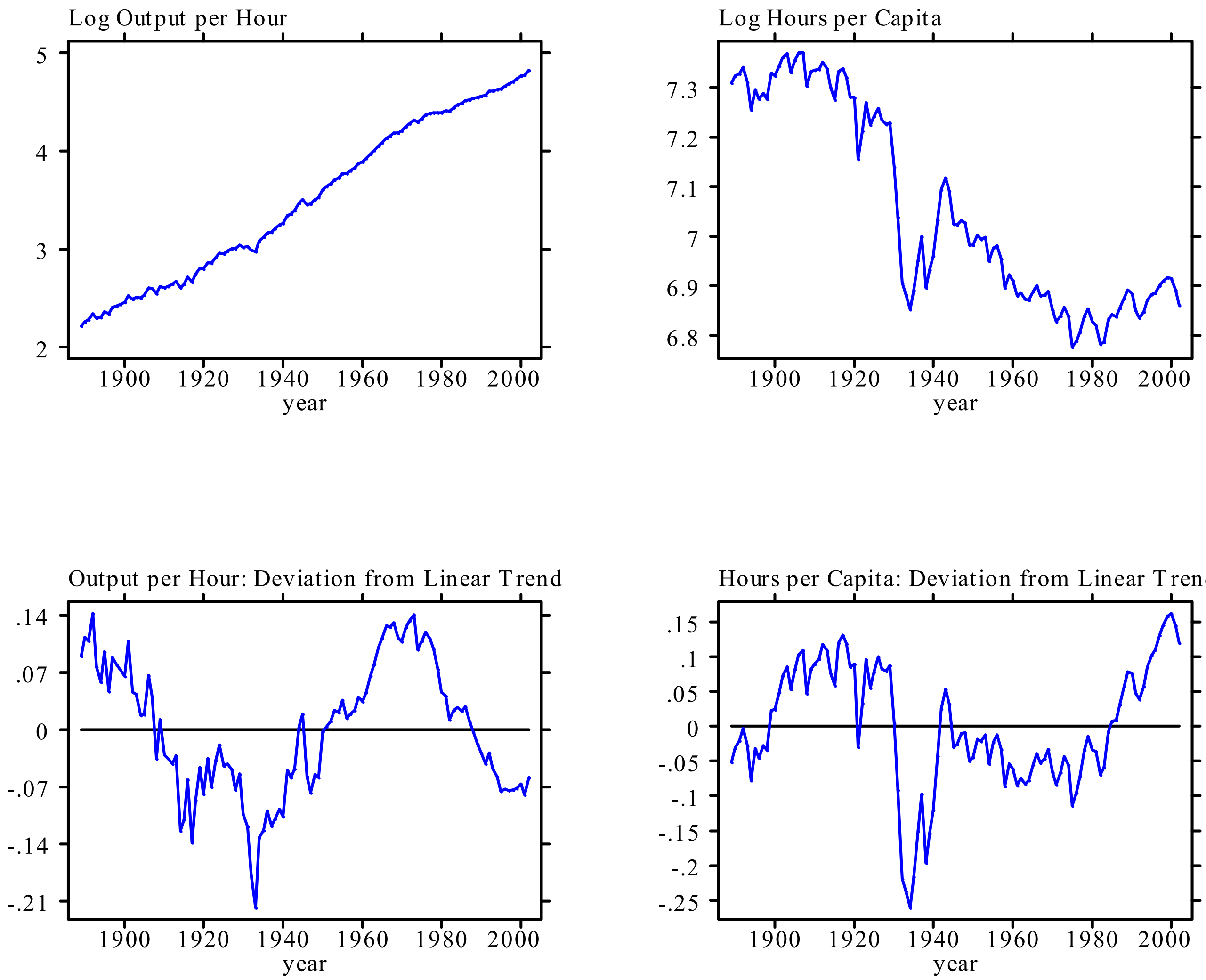


Figure 2
Responses to Technology Shock in a Bivariate Model
(90% standard error bands)

Figure 2A

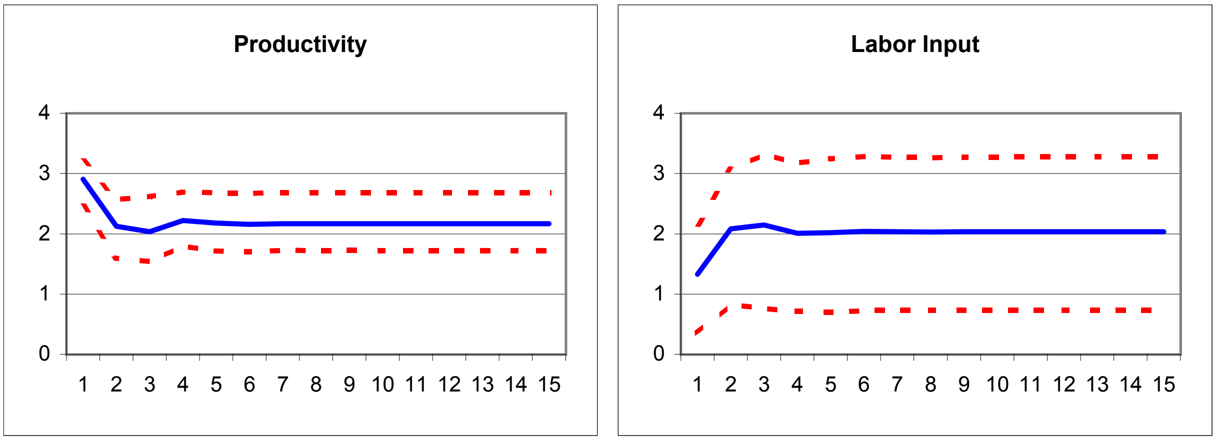


Figure 2B

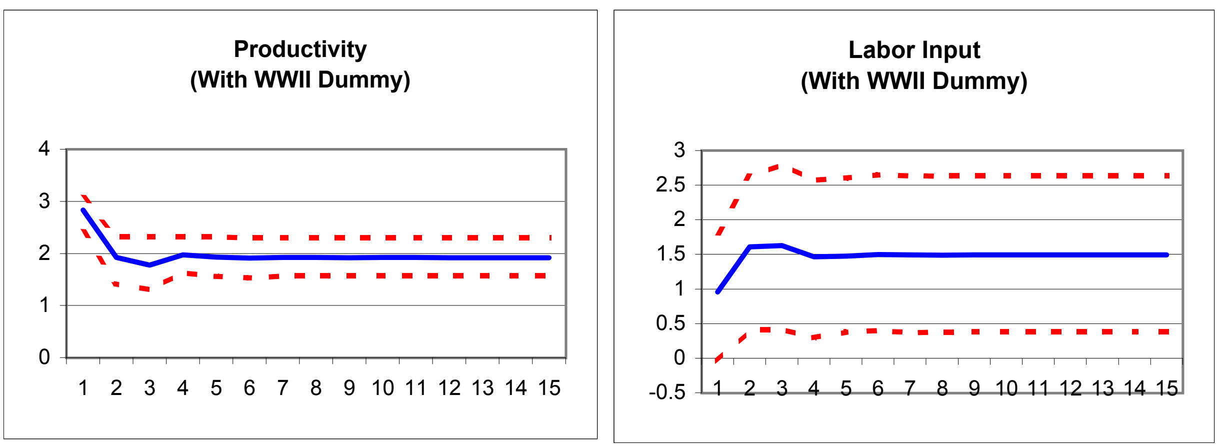


Figure 3
Responses to Technology Shock from Subsamples
(90% standard error bands)

Figure 3A

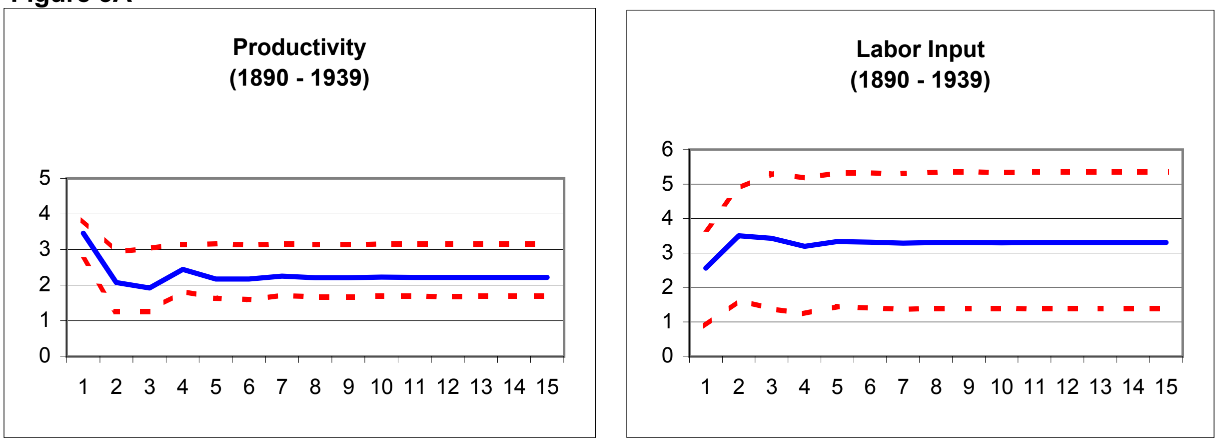


Figure 3B

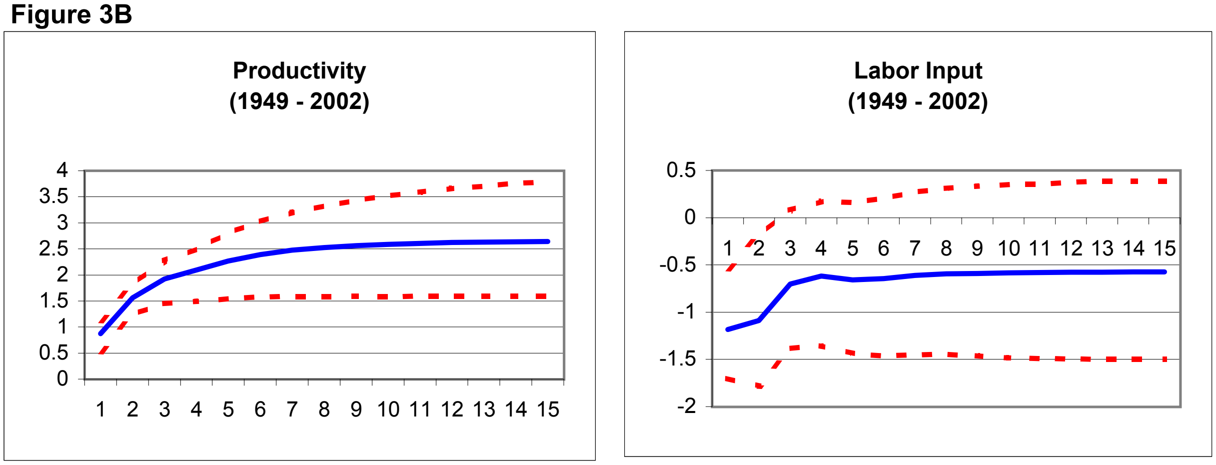


Figure 4
Impulse Responses to a Technology Shock
(Linearly Detrending Hours)

Figure 4A: Full Sample

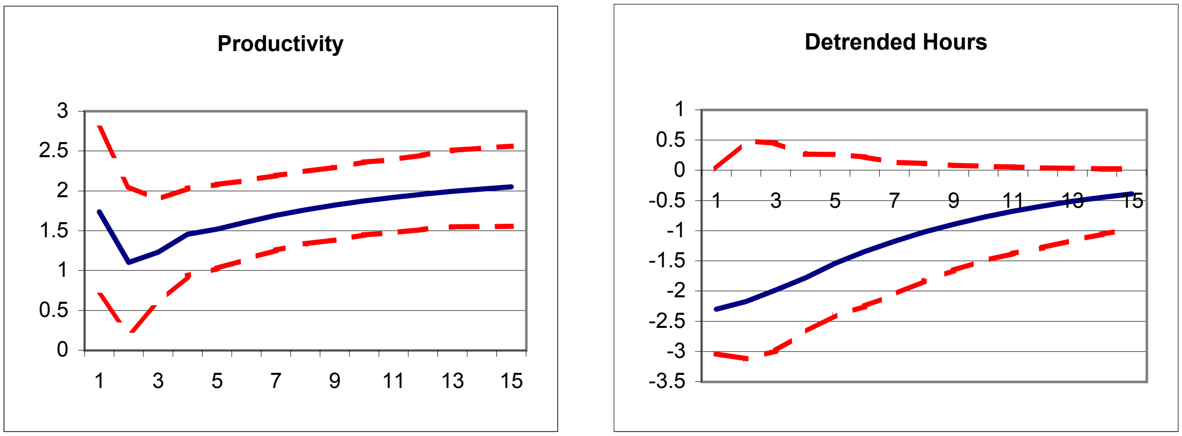


Figure 4B: Prewar Sample

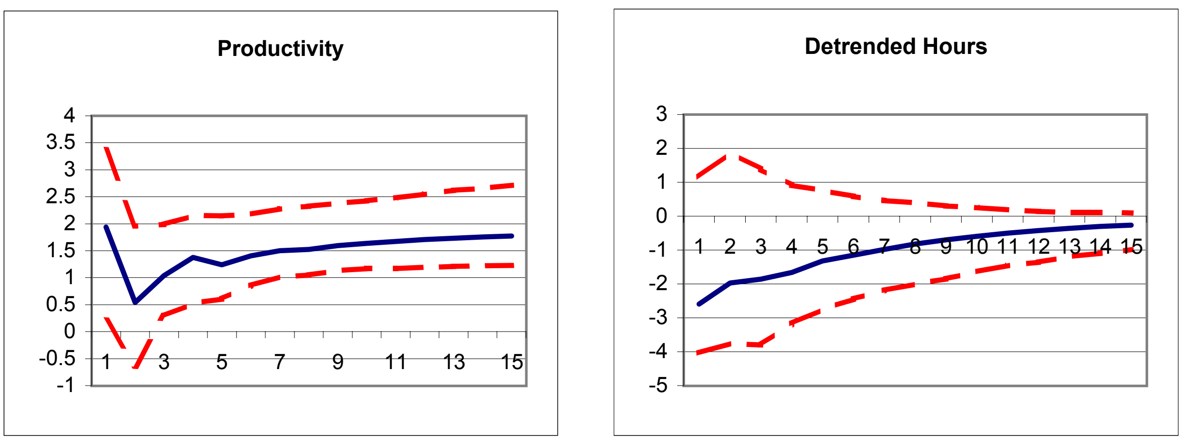


Figure 4C: Postwar Sample

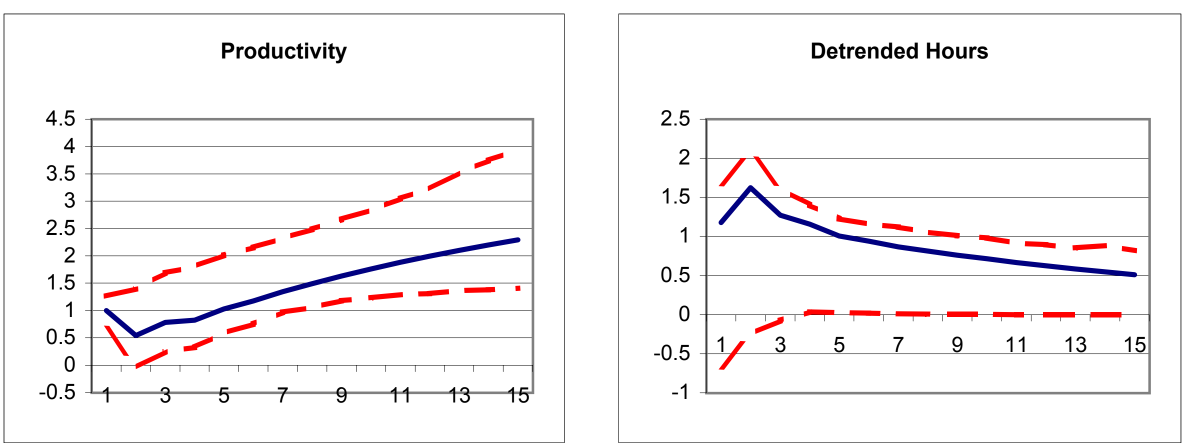
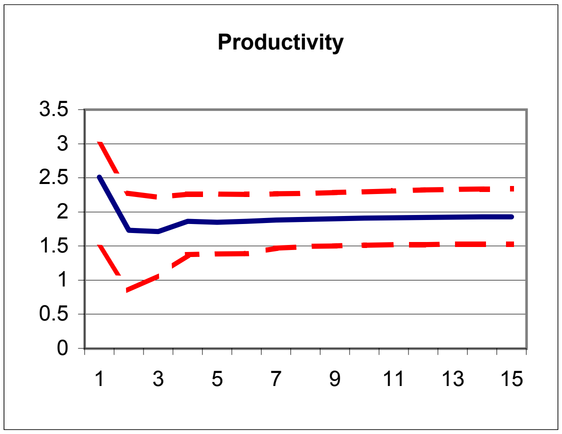


Figure 5
Impulse Responses to a Technology Shock
(Quadratically Detrending Hours)

Figure 5A: Full Sample



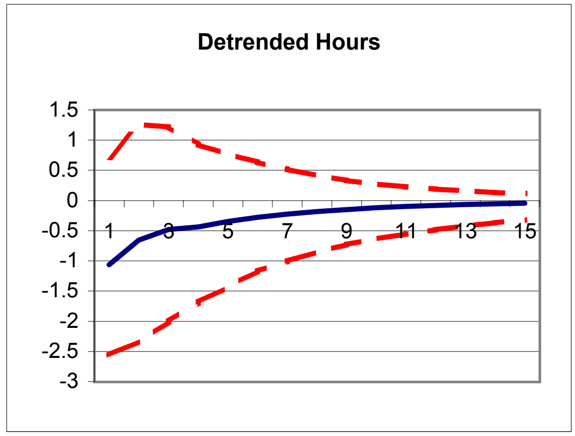
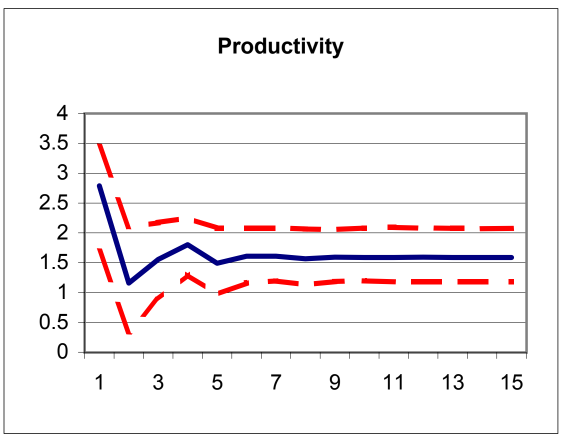


Figure 5B: Prewar Sample



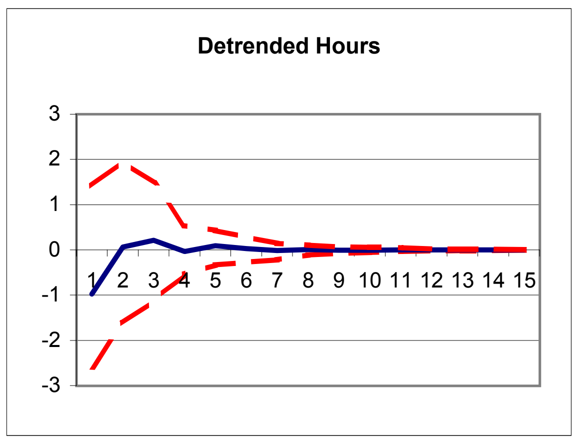
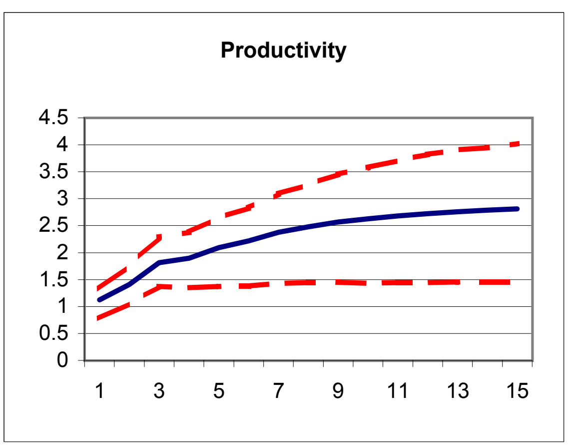


Figure 5C: Postwar Sample



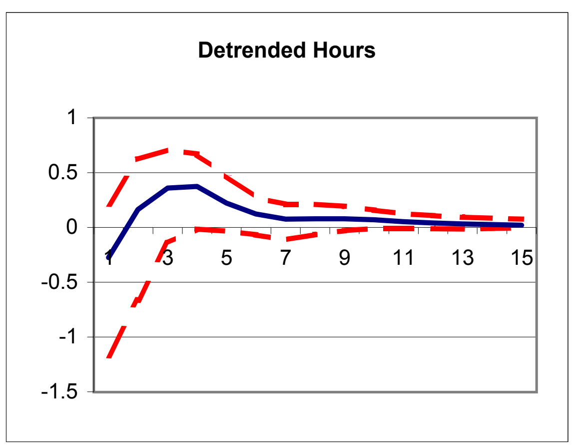


Figure 6
Impulse Responses to a Technology Shock
(Hybrid Model Specification)

Figure 6A: Full Sample

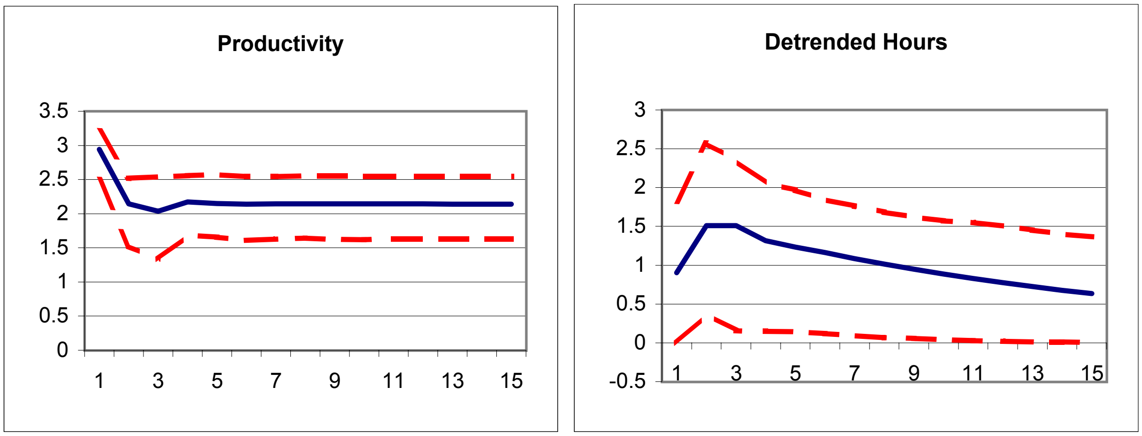


Figure 6B: Prewar Sample

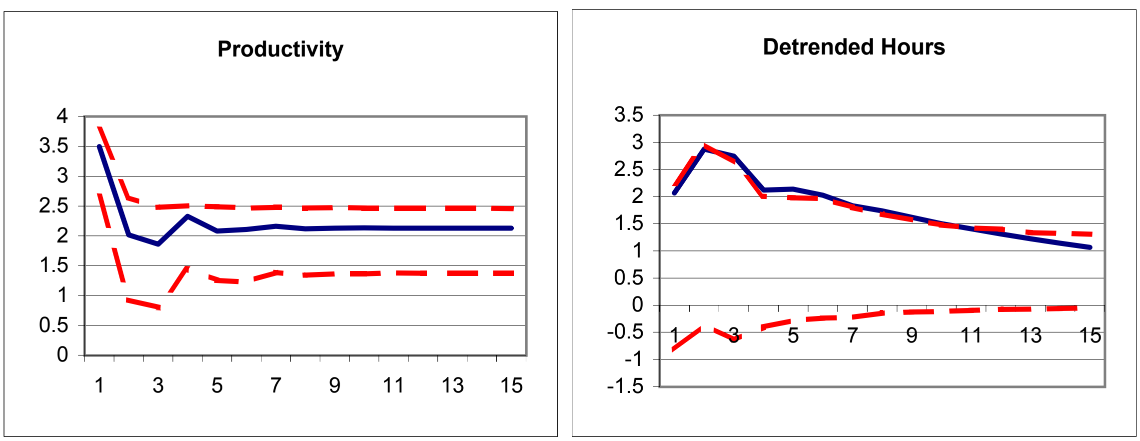


Figure 6C: Postwar Sample

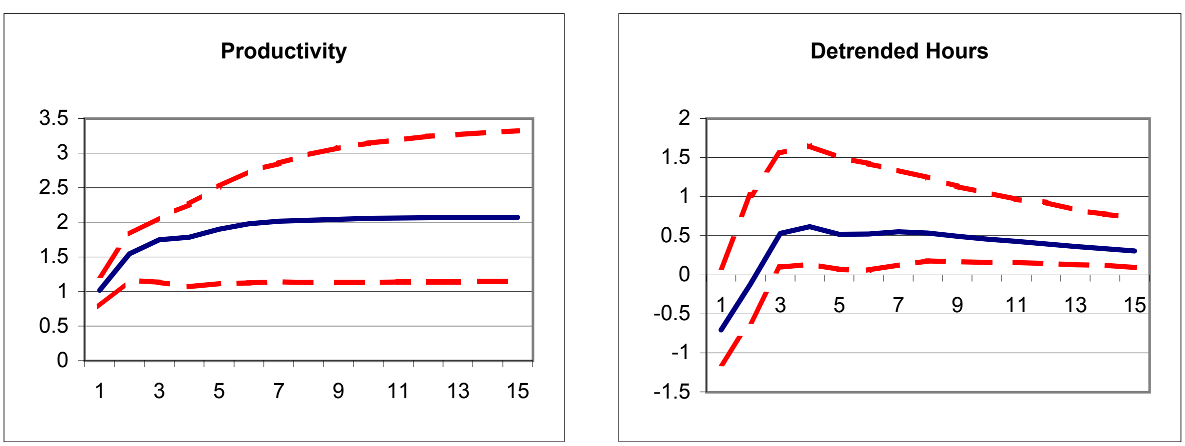


Figure 7: Impulse Responses to Non-Technology Shocks

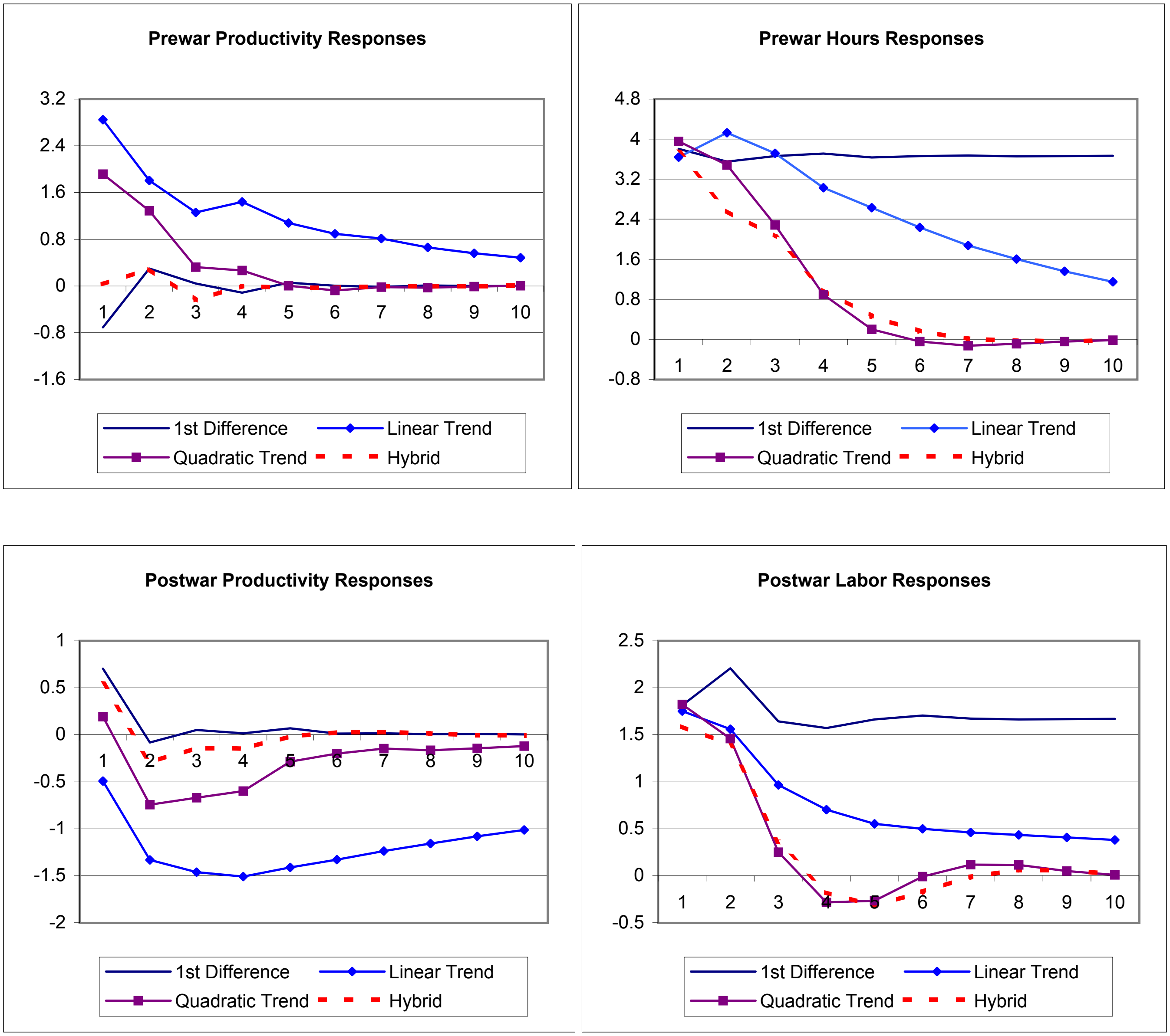


Figure 8: Plots of Technology Shocks

Figure 8A

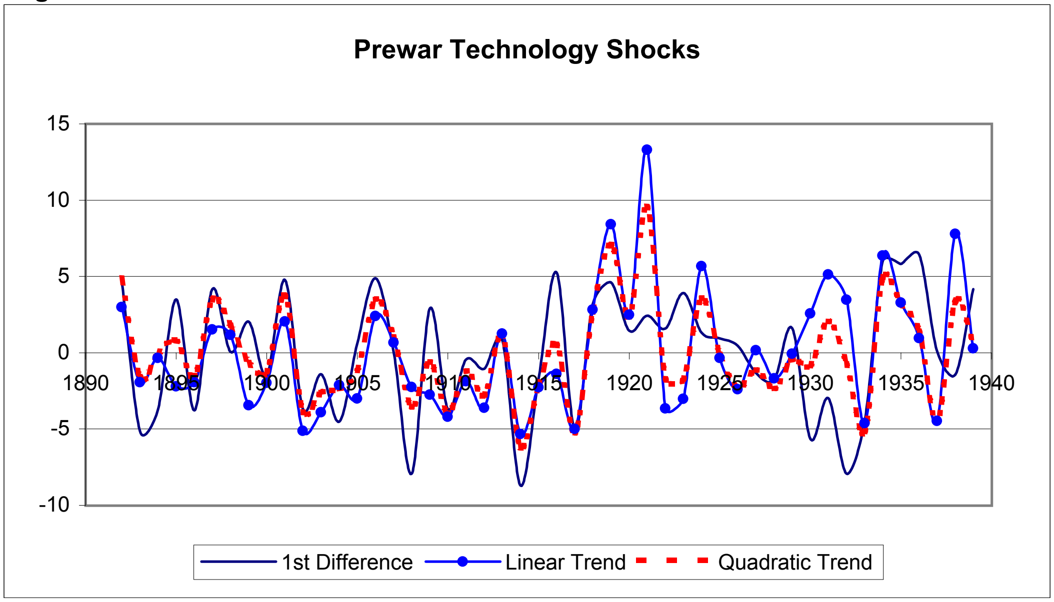


Figure 8B

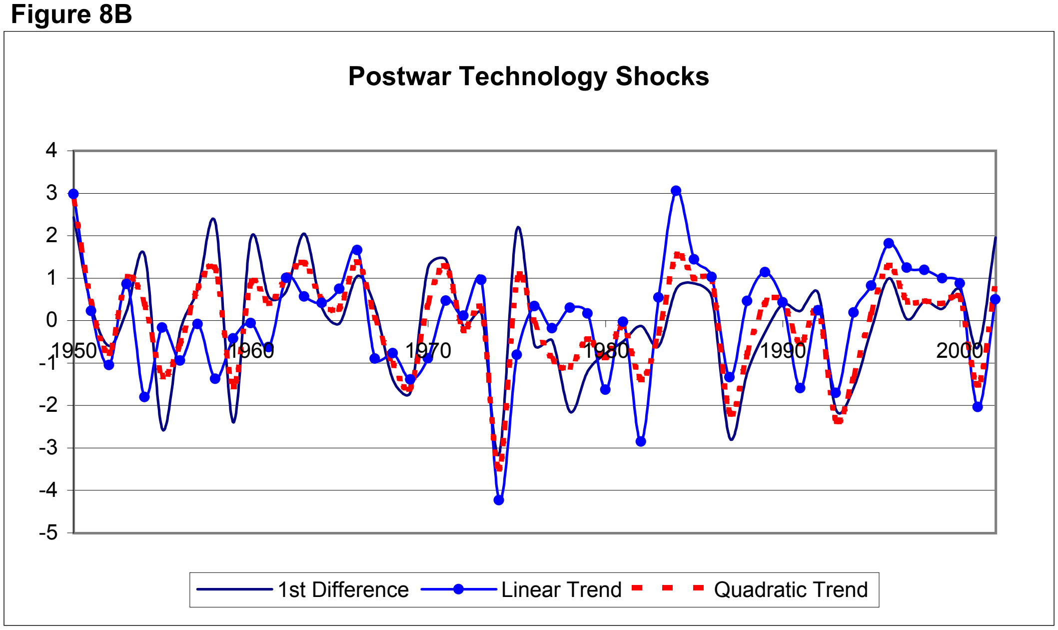


Figure 9A
Responses to Technology Shock: Full Sample
(5 Variable Model, 90% Confidence Bands)

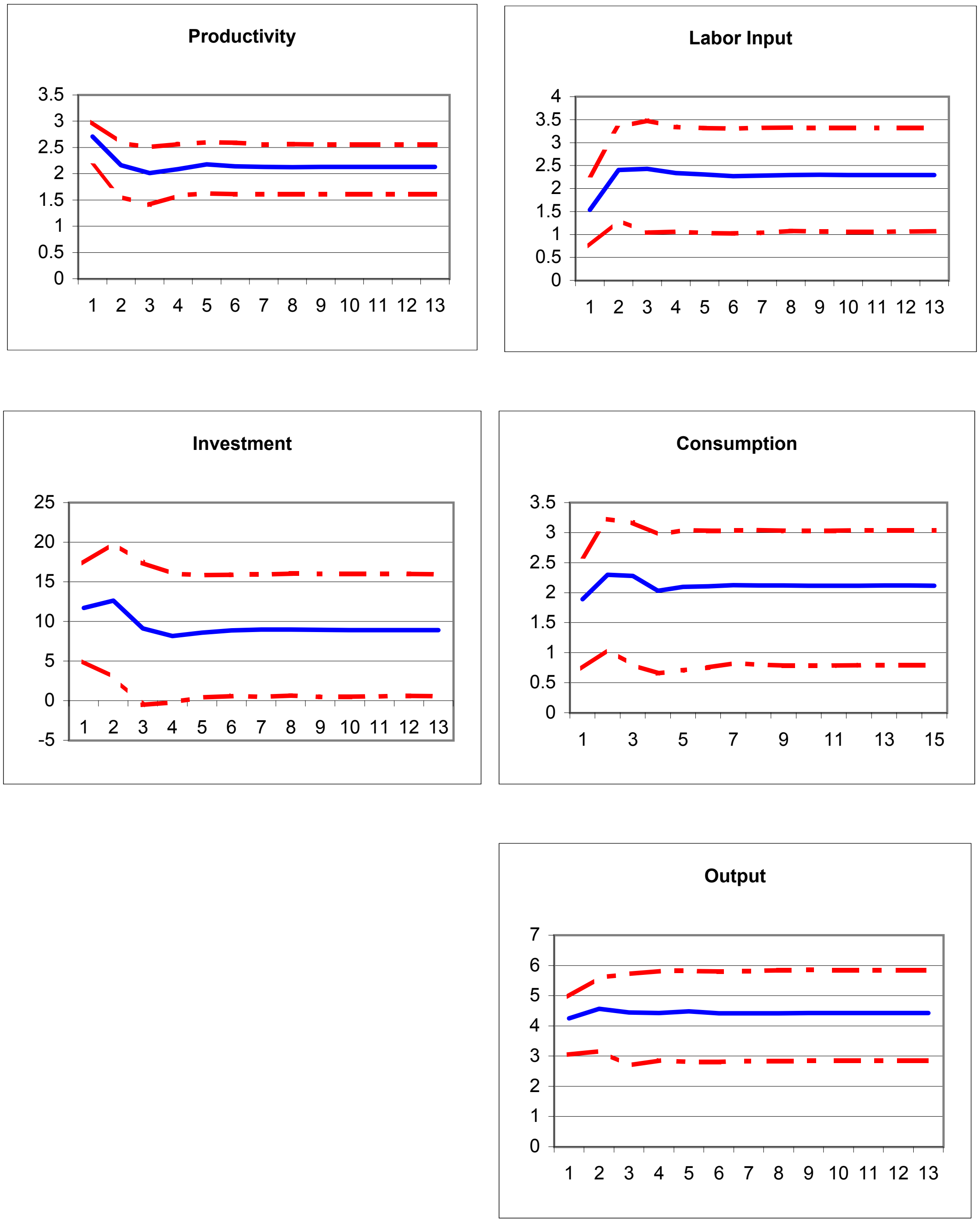


Figure 9B
Responses to Technology Shock: Prewar Sample
(5 Variable Model, 90% Confidence Bands)

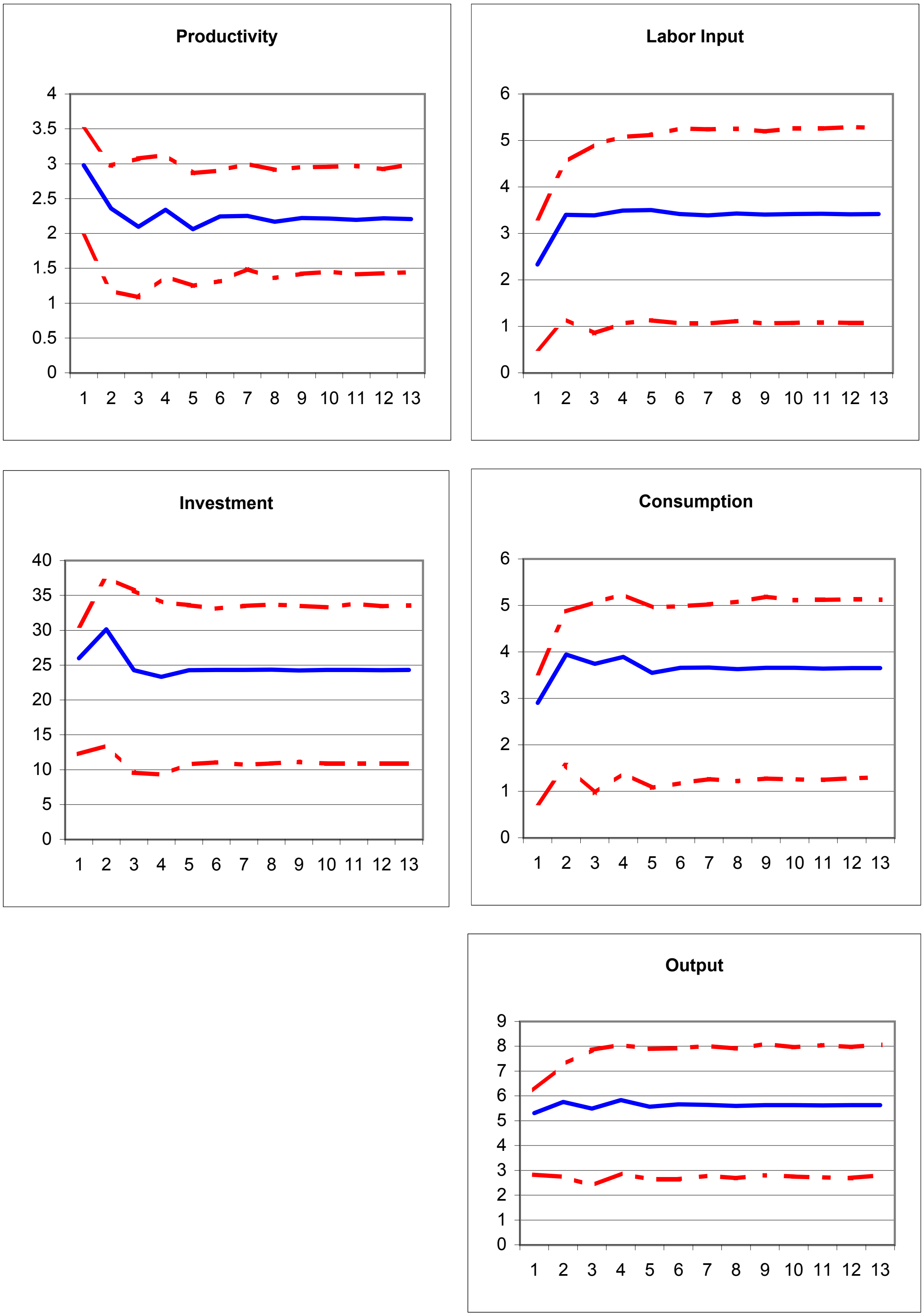


Figure 9C
Responses to Technology Shock: Postwar Sample
(5 Variable Model, 90% Confidence Bands)

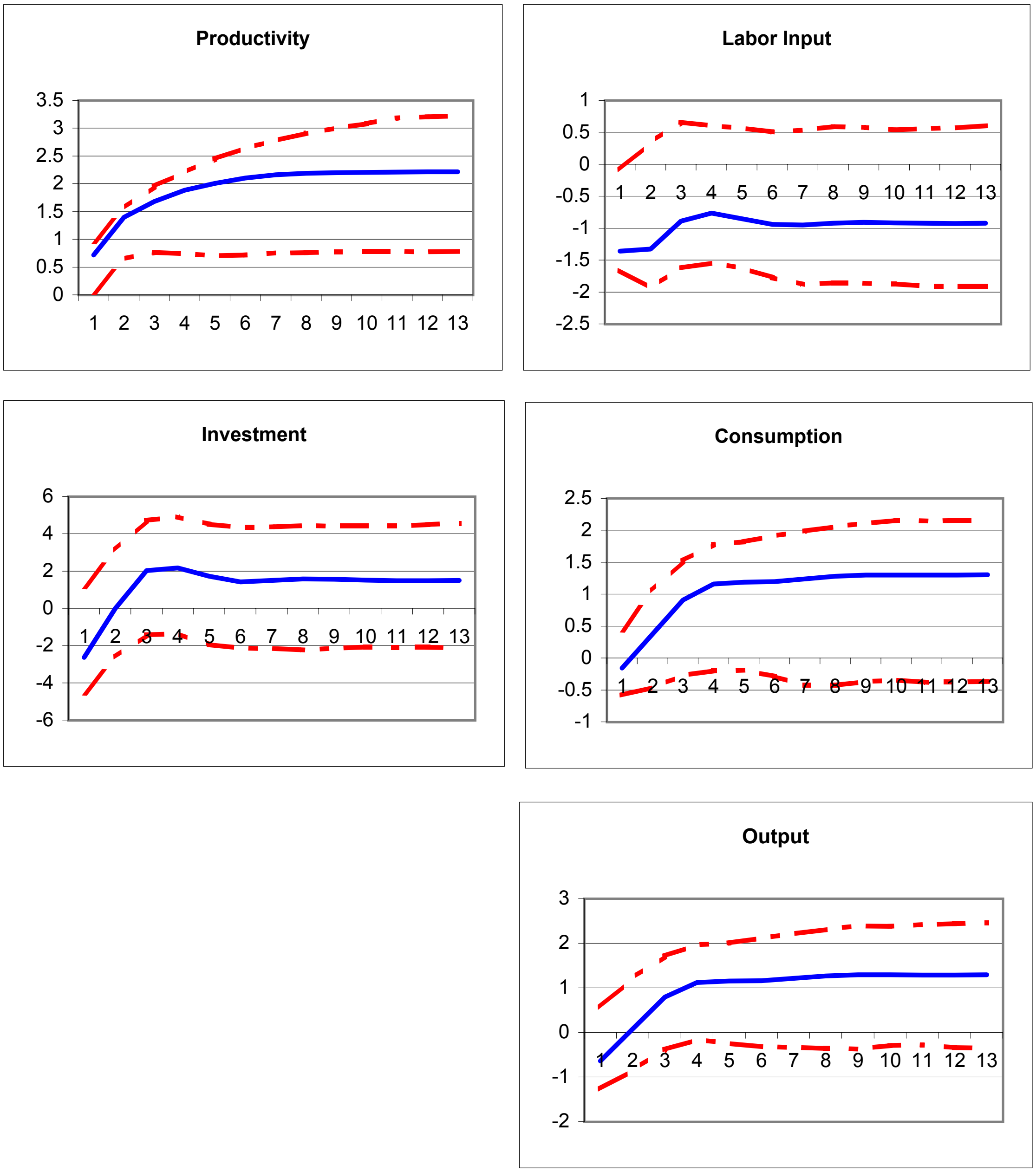


Figure 10A
Plot of Technology Shocks

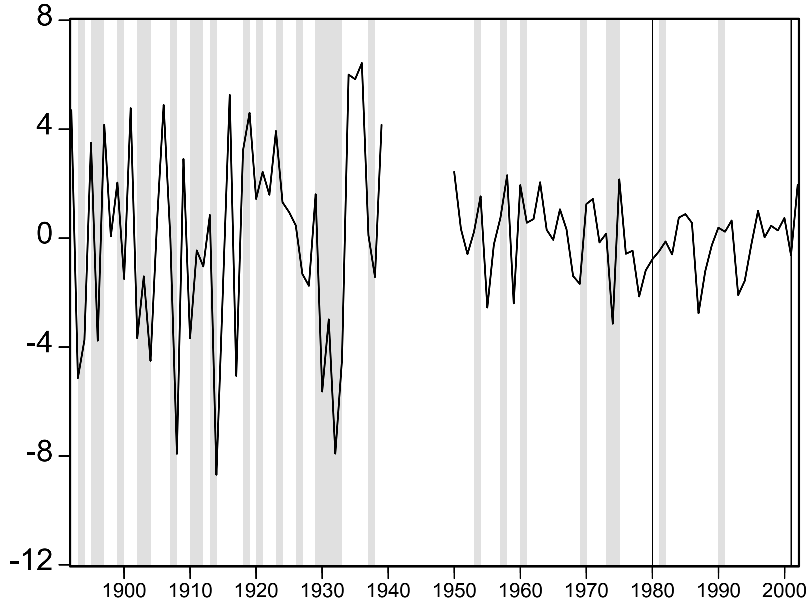


Figure 10B
Plot of Non-technology Shocks

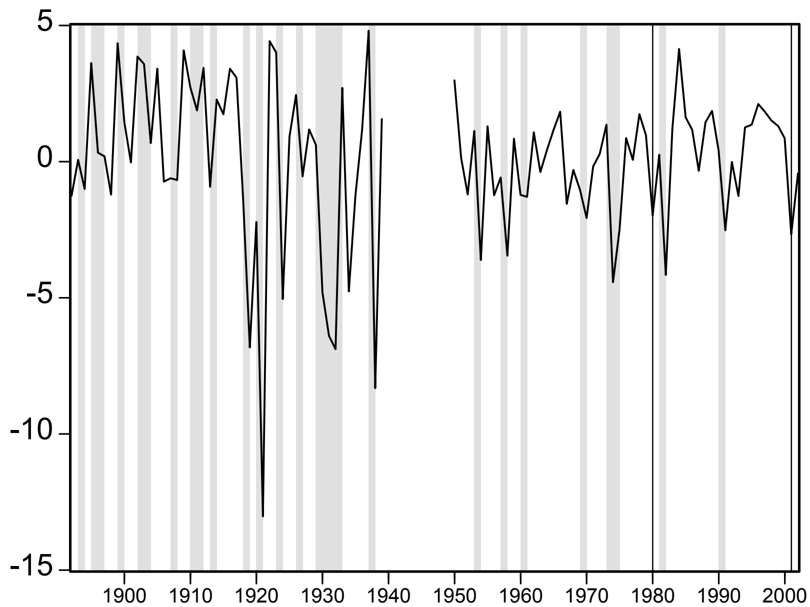
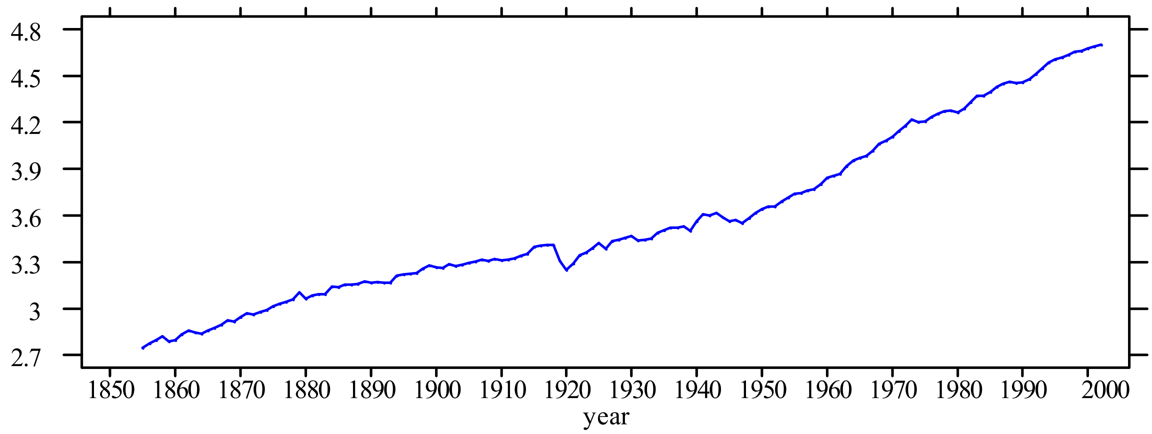


Figure 11: UK Data

Output per Worker



Employment per Capita

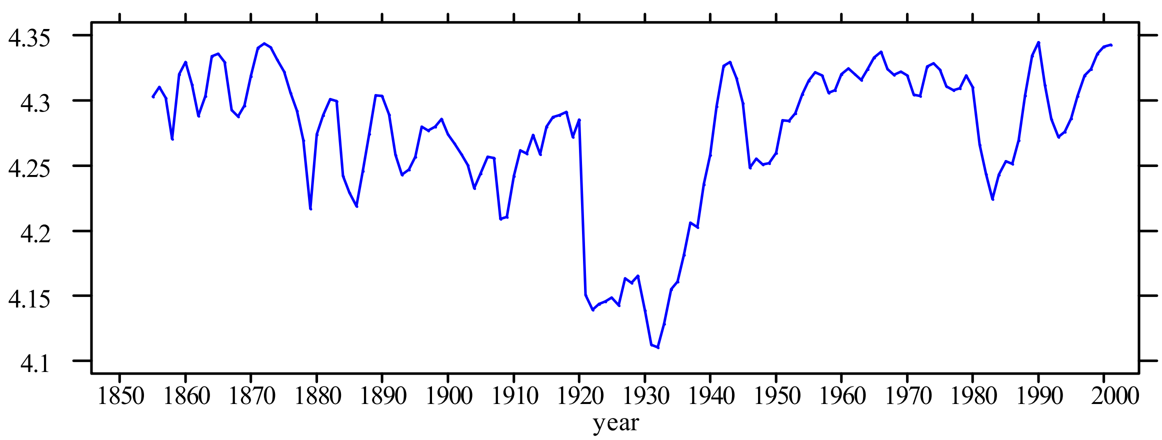


Figure 12: Historical UK Impulse Responses to a Shock to Technology

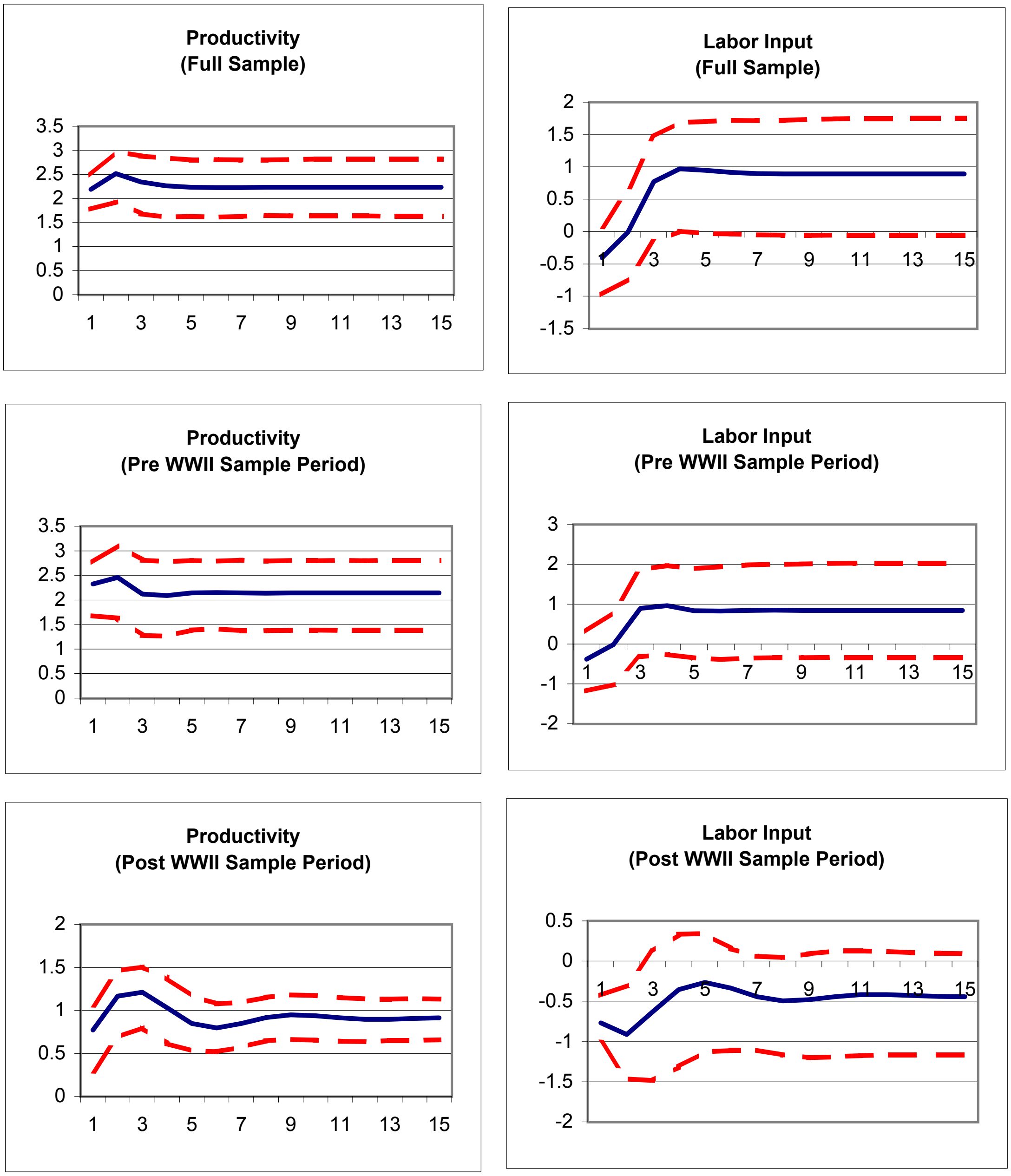


Figure 13A
UK Technology Shock

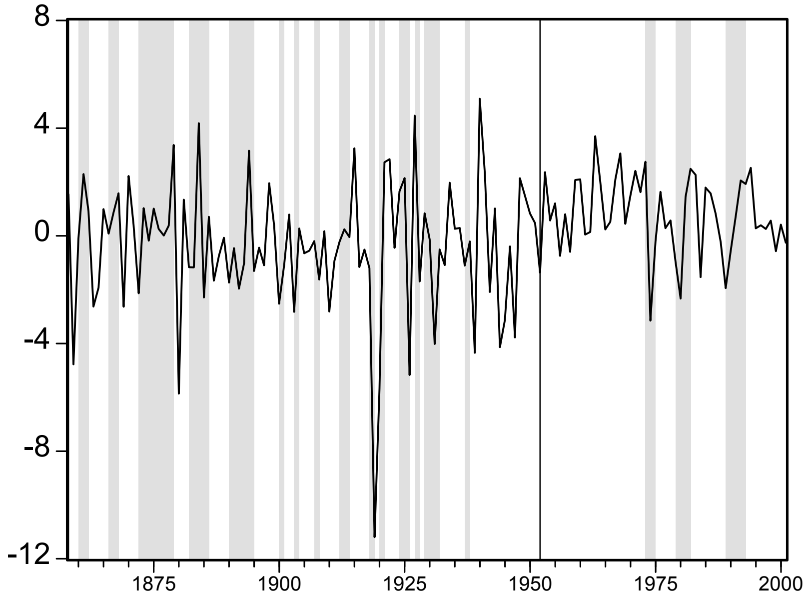
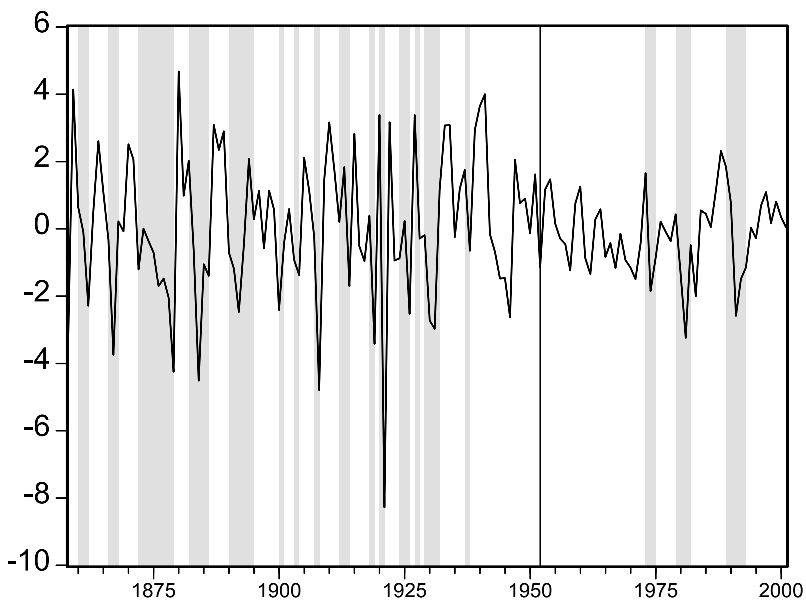
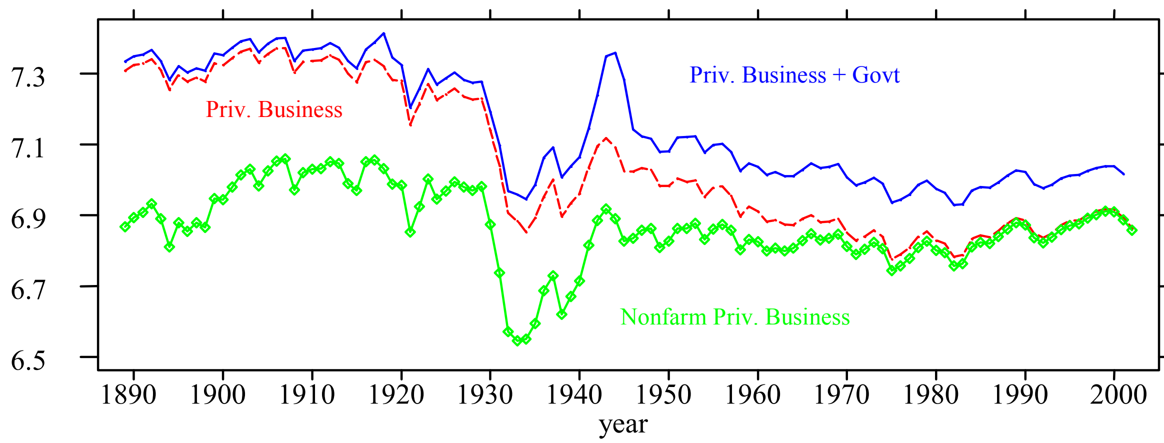


Figure 13B
UK Non-Technology Shocks

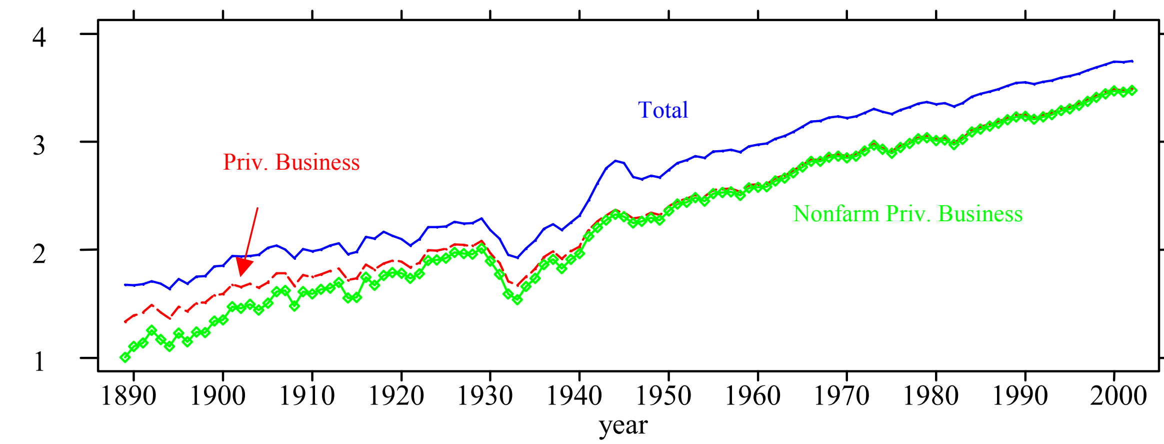


Data Appendix Figure: US Historical Patterns, 1889-2002

A. Log Hours per Capita



B. Log Real GDP per Capita



C. Log Output per Hour