Effects of Productivity Shocks on Hours-Worked: UK Evidence*

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Abstract

We provide evidence that positive industry-level productivity shocks cause hours-worked to fall in the short run in the UK economy. We use UK industry data, which covers both manufacturing and non-manufacturing industries, and identify productivity shocks using long-run restrictions and structural vector autoregression methodology. Our findings show that the unconditional correlation between growth rates of productivity and hours is negative in almost all the industries, and the correlation conditional on productivity shocks is negative in over three-quarters of the industries. After a positive productivity shock, hours fall in 26 of the 31 industries. The findings at the aggregate level are consistent with those at industry level. We note some striking differences in comparison to the recent US literature. Significantly larger capital adjustment costs in the UK help account for the UK-US differences. Moreover, UK industries with higher investment elasticities (lower capital adjustment costs) have less negative impact effects of hours.

JEL classification: E32, E24

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1 Introduction

What are the employment effects of productivity shocks at the industry level? This question is interesting for at least two reasons. First, whether employment (measured as total hours worked) rises or falls after a positive productivity shock can help delineate the class of macroeconomic models which predict this effect. This information can be helpful for macroeconomic policy considerations, quite apart from the issue of whether productivity shocks themselves are or are not a prime source of aggregate fluctuations. Second, recent evidence from the US industry data has led to opposite conclusions. Basu et al. (2006), using Dale Jorgenson's annual KLEM data from 1949-1996, find that in 22 of the 29 industries examined, total hours worked falls after a positive shock to total factor productivity (TFP). By contrast, Chang and Hong (2006), using the annual NBER-CES Manufacturing Industry Database over the 1958-1996 period, find that in over two-thirds of the two-digit industries, total hours worked rise after a positive TFP shock.[1] It is of interest to bring to bear evidence from other industrialized countries in gaining a broader perspective on this topic. These reasons are the motivation for this paper.

Our objective is to determine the short-run effects of productivity shocks on total hours worked in the UK at the industry level.[2] To our knowledge ours is the first paper to conduct this study. We use the annual Bank of England Industry Data (BEID) available for the 1970-2000 period for our analysis. Oulton and Srinivasan (2005) provide a detailed description of the data construction methodology. One of the advantages of this data is that it covers broad sectors of the UK economy, which include agriculture, mining, manufacturing, and services. We can, therefore, determine the employment effects beyond the narrow and declining manufacturing sector alone. To identify productivity shocks, we follow the Galí (1999) identification scheme using the long run restrictions within the structural vector-autoregression (SVAR) framework. Chang and Hong (2006) use a similar methodology to identify industry-level productivity shocks in the US. In particular, we assume that only industry level technology shocks can have a permanent effect on the level of that industry's

[1] Earlier work of Kiley (1998) used industry-level labour productivity and found that employment falls in the US manufacturing industries after a positive productivity shock. Chang and Hong (2006), however, point out that TFP is a superior measure of productivity than labour productivity as the latter is confounded by changes in input mix. Shea (1998) used R&D data and found that employment rises in the short run but falls in the long-run after a positive productivity shock.

[2] Even though productivity may be affected by non-technology related shocks (such as the uncertainty shocks identified in Bloom (2009) and Alexopoulos and Cohen (2009b)), in this paper, we use the terminology 'productivity shocks' and 'technology shocks' interchangeably.

TFP in the long run.

We highlight three benchmark results. First, in 30 of the 31 industries the *unconditional* correlation between TFP growth and hours growth is negative (with significantly negative in 11 industries). Second, the correlation *conditional* on the productivity shock is negative in 25 of the 31 industries (with significantly negative in 21 industries). Third, total hours worked fall upon impact after a positive productivity shock in 26 of the 31 industries (with a significant fall in 14 industries). The second and third findings are based on a bi-variate SVAR methodology using TFP growth and hours growth. We examine robustness to a variety of checks suggested in the literature. In particular, we consider utilization corrected TFP, control for aggregate TFP shocks, consider a larger SVAR, quadratic detrended hours, markup adjusted TFP, and the effects of capital taxation. The benchmark findings on conditional correlations and impact effects are robust in all of these cases. Overall, our results suggest that UK industry hours falls in the short run after a positive technology shock.

Interestingly, in the UK the employment effects of productivity shocks at the aggregate level are consistent with those at the industry level.[3] At both industry and aggregate levels, favourable productivity shocks induce a short-run fall in hours in the UK. This finding is consistent with the findings of Basu et al. (2006) for the US.[4] Relative to Chang and Hong (2006), we highlight two points based on our results. First, sectoral technology shocks identified using TFP growth have a contractionary effect on hours in the majority of the industries. In this respect, the industry-level UK evidence is in sharp contrast to their US findings. Second, sectoral technology shocks identified using labour productivity growth also have a contractionary effect on hours in most industries, consistent with their findings. Thus, unlike the US, labour productivity and TFP in the UK do not appear to behave very differently at the sectoral level in determining the effects of identified technology shocks on hours worked.

In theory, positive productivity shocks in real business cycle models with real rigidities (Francis and Ramey (2005)) or in sticky price models (Galí (1999)) can generate negative effects on hours.[5]

[3] Khan and Tsoukalas (2006) provide a detailed analysis of the sources of UK business cycles at the aggregate level using the SVAR methodology.

[4] The UK evidence at the aggregate level is consistent with the US evidence previously presented in Galí (1999), Francis and Ramey (2005), and more recently, some evidence in Alexopoulos and Tombe (2012) on the possible short run negative response of hours to innovations in management techniques.

[5] Wang and Wen (2011) present a real multi-sector model of entry and exit of firms with the time-to-build feature in which both employment and investment fall, and output rises on impact after a positive technology shocks. They argue that this model can match the empirical evidence in Basu et al. (2006) without necessarily invoking the price stickiness assumption.

There is evidence for a greater degree of real and nominal rigidities in the UK than in the US which helps explain why the negative effects of productivity shocks on hours are more pervasive at the industry level in the UK. For the UK industries, a key mechanism that provides an explanation of the result is the differences in capital adjustment costs across industries. We find evidence that industries with higher investment elasticities (lower capital adjustment costs) have less negative impact effect of hours.

The rest of the paper is organized as follows: In section 2 we describe the data and the empirical methodology. In section 3 we present the benchmark results and interpretation. Section 4 provides robustness checks and section 5 concludes.

2 Data and Empirical Methodology

In this section we describe the data and the identification scheme underlying our empirical methodology.

2.1 Data

The industry data are from the BEID. It is an annual industry-level dataset for the period 1970-2000. The data are for 34 industries covering the whole economy, of which 31 industries are in the market sector. It covers both manufacturing and service industries. We exclude the three public sector industries, namely, public administration and defence, education, and health and social services (numbered 30, 31, and 32 in the BEID). A detailed description is available in Oulton and Srinivasan (2005). Our benchmark findings use data on total factor productivity (TFP) growth and total hours worked adjusted for quality, for each industry. Chang and Hong (2006) argue in favour of using TFP growth instead of labour productivity as the latter is influenced by changes in the input mix. To facilitate comparison of our findings with those of Chang and Hong (2006) and Basu et al. (2006) we have chosen to work with the TFP measure as the benchmark and examine robustness with respect to the labour productivity measure.

The importance of correcting for utilization effects in measured TFP has long been stressed in the literature (see, for example, Burnside et al. (1995) and references therein). Following the methodology of Basu et al. (2006), Groth et al. (2006) corrects measured industry TFP in the BEID of utilization (capital and labour) effects. Under the Basu et al. (2006) methodology one can derive a relationship between the unobservable industry-level utilization and observable variables using the first-order-conditions of an industry cost minimization problem. The parameters associated with the observables can then be estimated. The corrections provided in Groth et al. (2006) are, however, based on six sub-groups of industries in the BEID covering 30 of the 31 industries in our analysis. It may, therefore, be useful to check the results for both with and without utilization corrections. It can, for example, reveal whether or not the employment effects are driven by utilization effects alone. For this reason, we use the utilization corrected TFP as a robustness check and consider the standard measure in the benchmark estimation. We conduct further robustness checks to ensure that the identified industry-level productivity shocks are not capturing aggregate shocks or driven by input-mix variations. For these checks, we use data on aggregate TFP and industry-level data on real gross output, real value added, capital-labour ratio, material-labour ratio, capital share, and material share. Additionally, we use aggregate data to provide the corresponding findings at the aggregate level. We indicate the aggregate variables and their source in section 4.5 below.

2.2 Identification of productivity shocks

We consider the identification of technology shocks using long-run restrictions within the SVAR framework, as in Galí (1999).[6] The main identifying assumption is that only productivity shocks can have a permanent effect on the level of TFP in the long run. Since our focus is on industry analysis, our empirical methodology follows Chang and Hong (2006), which also helps us to contrast their findings for the US economy. The empirical validity of the identification assumption requires that the level of TFP exhibits a unit root. Table 1 reports the unit root tests based on the Augmented Dickey-Fuller test. The null of unit root is not rejected in any of the industries (for lags two to four). We report results for lags one to five but the optimal lag for all industries lies between two and four. Based on this finding the empirical analysis can proceed.

We consider a bivariate VAR specification for our benchmark results. The empirical structural model of industry i is given as (where the industry subscript is dropped for convenience)

$$\begin{bmatrix} \Delta TFP_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^o \end{bmatrix} \equiv C(L)\varepsilon_t = \sum_{j=0}^{\infty} C_j \varepsilon_{t-j} \tag{2.1}$$

where Δ is the first-difference operator, ΔTFP_t denotes growth rate of total factor productivity,

[6]See, for example, Shapiro and Watson (1988), Blanchard and Quah (1989), and King et al. (1991) for early contributions to the SVAR literature.

Δh_t denotes growth rate of hours-worked, ε_t^z is the productivity shock (to be identified), ε_t^o is the non-productivity shock (unidentified), $E[\varepsilon_t \varepsilon_t^{'}] = I$, $E[\varepsilon_t \varepsilon_s^{'}] = 0$, for $t \neq s$, and L is the lag-operator. We can state the long run identifying assumption described above as $C^{12}(1) = \sum_j^{\infty} C_j^{12} = 0$.

The reduced-form moving average representation associated with (2.1) is

$$\begin{bmatrix} \Delta TFP_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} A^{11}(L) & A^{12}(L) \\ A^{21}(L) & A^{22}(L) \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \equiv A(L)e_t = \sum_{j=0}^{\infty} A_j e_{t-j} \tag{2.2}$$

with $A_0 = I$, $E[e_t e_t^{'}] = \Omega$, $E[e_t e_s^{'}] = 0$ for $t \neq s$, and $\Omega = C_0 C_0^{'}$, $e_t = C_0 \varepsilon_t$, and $C_j = A_j C_0$. The empirical implementation of (2.2) proceeds by estimating a VAR

$$\begin{bmatrix} \Delta TFP_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} B^{11}(L) & B^{12}(L) \\ B^{21}(L) & B^{22}(L) \end{bmatrix} \begin{bmatrix} \Delta TFP_{t-1} \\ \Delta h_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{2.3}$$

In SVAR specifications similar to (2.1) using aggregate US data on labour productivity and hours, whether hours enter (2.1) in levels or growth rate can influence the short-run effects of productivity shocks on hours, as highlighted by Christiano et al. (2003). Hours tend to rise under the level-specification and fall under the growth rate-specification after a positive technology shock. More recently, however, Fernald (2007) shows that once the observed low frequency correlation between labour productivity and hours (in levels) in the US data is accounted for, then whether hours are treated as stationary (and enter (2.1) in levels) or as non-stationary (and enter (2.1) in first-differences) does not lead to different conclusions. It turns out that the low frequency correlation is somewhat less of an issue in the UK data. In the aggregate UK data, Khan and Tsoukalas (2006) show that hours fall after a positive technology shock under both specifications even without accounting for the low-frequency correlation. In the industry SVAR specification (2.1), we use the growth rate of hours. This choice is based on the results for the ADF tests reported in Table 1. We find strong evidence for the non-stationarity of hours in all UK industries. This evidence is also consistent with Chang and Hong (2006) who find similar non-stationarity of hours in two-digit US industries and use the growth rate specification in their analysis.

In estimating (2.3) the Akaike Criterion indicates an optimal lag of one for all industries. After estimating the elements of $\widehat{C(L)}$, we can identify the industry level productivity shocks. Next, we examine the impact effect of hours to such shocks in each industry and, as in Galí (1999) and Chang and Hong (2006), compute the correlation between productivity growth and hours growth, conditional on the productivity shock, using the formula

$$\mathrm{Corr}(\Delta TFP_t, \Delta h_t|z) = \frac{\mathrm{Cov}(\Delta TFP_t, \Delta h_t|z)}{\sqrt{\mathrm{var}(\Delta TFP_t|z)\mathrm{var}(\Delta h_t|z)}} = \frac{\sum_{j=0}^{M} \widehat{C_j^{1z}}\widehat{C_j^{2z}}}{\sqrt{(\sum_{j=0}^{M} \widehat{C_j^{1z}})^2(\sum_{j=0}^{M} \widehat{C_j^{2z}})^2}} \tag{2.4}$$

where M is the truncation lag, $\mathrm{Cov}(\Delta TFP_t, \Delta h_t|z) = \sum_{j=0}^{M} \widehat{C_j^{1z}}\widehat{C_j^{2z}}$ is the conditional covariance of TFP growth and hours growth, $\mathrm{var}(\Delta TFP_t|z) = (\sum_{j=0}^{M} \widehat{C_j^{1z}})^2$ is the conditional variance of TFP growth, and $\mathrm{var}(\Delta h_i|z) = (\sum_{j=0}^{M} \widehat{C_j^{2z}})^2$ is the conditional variance of hours growth.[7] The standard errors for the conditional correlations and the confidence interval for the impact effects are computed using bootstrap simulations with 500 random draws.

3 Results

Table 2 presents the benchmark results. Column 2 reports the unconditional correlation between TFP growth and hours growth. In 30 of the 31 industries the unconditional correlation is negative. Of these 30 industries, the negative correlation is statistically significant in 12 industries at the 5-percent level. In 25 of the 31 industries the conditional correlation between the two variables is negative. And in 21 of those 25 industries, the conditional correlation is statistically significant at the 5-percent level, and highly negative for several industries.[8] Thus, positive conditional correlation is found in only 6 of the 31 industries, and statistically significant in 2 of those 6 industries. Turning to the impact effects, we find that in 27 industries a positive technology shock leads to a fall in hours. In 14 of these 27 industries the negative response is also statistically significant. In only 3 industries the response of hours is positive, although not statistically significant at the 5-percent level.

One concern raised in the literature is whether the technology shocks identified using long-run restriction reflect changes in capital taxation rather than technology (Uhlig (2004)). To check this, we used data on UK dividend tax from McGrattan and Prescott (2004) and regressed the identified TFP shock from the benchmark specification on a constant and the change in the dividend tax rate.[9] The estimated coefficient turns out to be statistically insignificant at the 10-percent level

[7] Note that we use z to indicate that the correlations are conditional on the productivity shock ε_t^z.

[8] In many industries the estimated negative covariance between TFP growth and hours growth, conditional on the productivity shock, is about the same magnitude as the respective conditional variances in the two series, leading to highly negative conditional correlations. Previously, a similar high negative conditional correlation in the UK aggregate data was reported in Galí (1999) who found that the conditional correlation between labour productivity growth and employment growth from 1962:1 - 1994:3 was -0.91.

[9] We thank Ellen McGrattan for kindly providing us with this data.

for all the industries except the Business Services industry (industry 29). So the overall evidence suggests that changes in capital taxation are not an serious issue in most industries, except Business Services, and that the identified shocks reflect technology shocks. Overall, the combined evidence indicates that positive industry-level productivity shocks cause hours to fall in the short run.

3.1 Comparison with US findings

It is of interest to compare the response of hours to technology shocks in the UK industries with those found in the US industries. However, a straightforward industry-by-industry comparison is not feasible for the following reasons. First, Chang and Hong (2006) provide only a general summary of the impact effect of hours (their Table 2). Second, the results for the UK are for the whole economy while the findings for the US provided by Chang and Hong (2006) are for the manufacturing sector alone. Third, even when restricting to manufacturing industries, the total number of two-digit manufacturing industries is 20 for the US (of which 10 are non-durables and 10 durable goods manufacturing) and 11 for the UK (6 durable and 5 non-durable). Moreover the names of the industries do not exactly match. For these reasons, we can only provide a general comparison for the impact effect of productivity shocks on hours.[10] We, therefore, compare the summary of the industry level findings on conditional correlations and the impact effect of hours.

Panel A in Table 3 compares the conditional correlations across the non-durable and durable goods industries. For the UK, all 5 non-durable goods industries have negative and statistically significant conditional correlations. And 5 of the 6 durable goods industries have negative and statistically significant conditional correlations. This contrasts with the US findings where most non-durable and durable goods industries have positive conditional correlations.

Panel B in Table 3 compares the findings for the impact effect on hours for the manufacturing sector when TFP growth is used as the productivity measure in identifying shocks. The differences are striking. In the US manufacturing, the response of hours is positive in over two-thirds of the manufacturing industries. By contrast, in the UK manufacturing sector, hours fall in 10 of the 11 industries (with 7 statistically significant responses). In the US only 6 industries display a fall in short-run hours after a productivity shock (with 1 statistically significant).

Panel B in Table 3 also compares the findings when labour productivity growth is used as the

[10] Basu et al. (2006) provide correlations between TFP growth and hours growth are at the sector (one-digit) level. The UK analysis we conduct is at the two-digit level.

productivity measure in identifying shocks. Chang and Hong (2006) have argued that TFP is a preferred measure of productivity at the sectoral level relative to labour productivity. They provide a decomposition of labour productivity under constant returns to scale as

$$\Delta(y-l)_t = \Delta TFP_t + \alpha_{m,t}\Delta(m-h)_t + \alpha_{k,t}\Delta(k-h)_t \tag{3.1}$$

where y is log gross output, h is log quality-adjusted labour input, m is log material input, k is log capital input, $\alpha_{m,t}$ is output elasticity of material input, and $\alpha_{k,t}$ is the output elasticity of capital input. Table 7 provides the decomposition of labour productivity growth based on (3.1). The average contribution to labour productivity from material-labour growth is substantial in most industries. The average contribution from capital-labour growth is relatively less. The pattern of decomposition is similar to that in the US reported in Chang and Hong (2006). To the extent that non-technology factors such as the relative factor prices have permanent effects on input-mix growth (the last two terms in (3.1)), shocks that affect labour productivity in the long run may not entirely reflect technology. Chang and Hong (2006) find that in manufacturing industries, technology shocks identified using the TFP measure have a positive impact on hours in most industries whereas the shocks identified using the labour productivity measure have a negative impact in most industries. They attribute the negative impact of permanent labour productivity shocks to arising mostly in turn due to permanent shocks to the material-labour ratio. In the UK, we find that shocks that have a long run effect on labour productivity also have a negative impact on hours-worked similar to the findings of Chang and Hong (2006) for the US.[11] With the labour productivity measure, hours fall in 9 of the 11 UK manufacturing industries (with 7 statistically significant responses) and 18 of the 20 US manufacturing industries (with 9 statistically significant responses).

Since in the UK both TFP shocks and labour productivity shocks have a negative short run effect on hours in majority of the industries (see Table 6, specification 6) the two measures do not appear to behave very differently at the sectoral level in determining the effects of identified technology shocks on hours. To examine the effects of input mix shocks we consider two bivariate VAR specifications with material-labour growth and hours growth, and capital-labour growth and

[11] In terms of correlations, for example, both unconditional and conditional correlations between labour productivity growth and hours growth for the Oil & Gas industry are negative and statistically significant for the labour productivity case. Thus, this particular case highlights the point in Chang and Hong (2006) that shocks that have a long run effect on input mix growth could also lower hours even when TFP shocks raise hours on impact (as shown in Table 2). Table 5 in the Appendix provides industry-by-industry labour productivity based results.

hours growth, respectively. In each specification, the identified positive shock raises material-labour ratio or capital-labour ratio in the long run. We find that input mix shocks tend to reduce hours in the short run in most industries.[12]. Unlike the US finding, therefore, *both* permanent shocks to TFP and input-mix account for the negative response to labour productivity shocks.

3.2 Aggregate results

Table 4 reports the results for the aggregate economy for the 1970-2000 period. We use the aggregate TFP series in the BEID along with a four-quarter average of aggregate hours data.[13] Interestingly, the findings at the industry level in the UK are consistent with those obtained at the aggregate level. In other words, a positive aggregate TFP shock leads to a fall in aggregate total hours in the short run, similar to the effects of industry-level productivity shocks on industry employment. This finding suggests that mechanisms that generate contractionary short-run effects of positive productivity shocks at the aggregate level may also be relevant at the industry level.

3.3 What factors might explain the differences in UK-US findings?

Previous literature has shown that aggregate hours can fall after a positive productivity shock in either real business cycle models with strong real rigidities such as capital adjustment costs (Francis and Ramey (2005)) or in sticky price models (Galí (1999) and Basu et al. (2006)). So, is it the case that UK has relatively larger capital adjustment costs and/or relatively greater degree of price stickiness?

The estimates of capital adjustment costs in the UK based on the BEID are provided in Groth (2008). These estimates show that capital adjustment costs are indeed significantly higher in the UK relative to the US. Specifically, the speed of adjustment of capital to its long-run equilibrium is 12 years compared to 4 years in the U.S (Shapiro (1986)). Thus, the greater real rigidity in the UK economy in the form of larger capital adjustment costs appears to be a key explanation for the UK-US differences in the short-run response of hours to technology shocks.

The evidence for UK-US differences in price stickiness, however, are less clear cut. Recent work of Bunn and Ellis (2012b) and Bunn and Ellis (2012a) based on detailed data underlying the

[12]See Table 6, Appendix.

[13]Khan and Tsoukalas (2006) report aggregate results for the UK based on quarterly data and labour productivity (output per worker hour) for the period 1964 to 2004. Francis (2009) reports findings using aggregate annual historical UK data.

producer (2003-2007) and consumer price (1996-2006) indices released by the ONS-UK, suggests that consumer goods prices are relatively more sticky in the UK compared to the US. The stickiness in producer goods prices is, however, similar to the US evidence.

3.4 Explaining UK industry results: the role of real and nominal rigidities

To shed some light on the mechanism that may help explain the UK results it is possible to examine whether the magnitude of the impact effect of hours is related the size of the real rigidity (capital adjustment costs) across industries and/or nominal rigidity (the degree of price stickiness) across industries.

We first consider the capital adjustment costs explanation. From theory, we expect that the higher the capital adjustment costs, the more negative impact effect on hours of technology shocks. To account for the heterogeneity in responses across industries we follow the normalization considered in Chang and Hong (2006). Specifically, we consider the impact effect on hours of a positive TFP shock that increases industry TFP by 1 percent in the long run. The estimates of UK capital adjustment costs provided in Groth (2008) are based on five industry sub-groups in the BEID, namely, (1) Utilities (industries 15 to 17), (2) Manufacturing (industries 4 to 14), (3) Construction, Hotels & Distribution (industries 18 to 21), (4) Transportation (industries 22 to 26), and (5) Other Business Services (industries 28, 29, and 34). These estimates are in terms of investment elasticities, that is, the elasticity of the variable costs with respect to investment, which is inversely related to the size of the capital adjustment costs.[14] If differences in capital adjustment costs are a relevant underlying mechanism, we would expect a positive correlation between investment elasticity and the impact effect of hours.

We examine the correlation between investment elasticity of the sub-groups and the impact effects of hours for the industries in those sub-groups. As noted earlier, identified technology shocks in the Business Services industry were significantly correlated with changes in dividend taxes. For this reason we focus on sub-groups (1), (2), (3), and (4). Figure 1 shows the investment elasticities and the average impact effect of hours for each sub-group of industries. There is a strong correlation, 0.88, between the investment elasticities and the impact effects. Based on this evidence, we conclude that the differences in the magnitude of capital adjustment costs across industries is a key mechanism

[14] Table 4 in Groth (2008).

that can help explain the UK findings.

Turning to nominal rigidities, since industry level estimates of average duration of price stickiness are not available for the UK it is not feasible to assess whether there is a systematic link between the hours response and price stickiness.[15] Although there is evidence of substantial price stickiness in both manufacturing and services sector, it remains unclear if price stickiness is an underlying mechanism that can explain the observed industry-level effects of productivity shocks on hours.

3.5 Sub-sample correlations

Are the negative unconditional correlations in the data (Table 2, column 2) driven by the events of the early 1980s in the UK? The UK economy experienced a sharp pickup in productivity from the 1970s to the early 1980s. Several explanations for this phenomenon are suggested in the literature (Cameron (2003)). Mis-measurement issues aside, there are two reasons for the increase in productivity that are considered in the literature. First, following the recession of 1980-81, much of the overmanning phenomenon or excessive labour hoarding got eliminated. Second, the weakening of institutional rigidities and trade union power, alongside the withdrawal of state subsidies during the Thatcher years. The national unemployment rate doubled from 6% to 12% from 1980 to 1984.[16] These structural changes could then cause the correlation between productivity growth and hours growth to to be potentially negative at the sectoral level. We compute the correlations for the two subsamples 1970-1985 and 1985-2000 as a simple way to check how the correlation has changed for the industries over time.[17] Table 5 reports the findings. Over the first sub-sample, 20 industries have a negative correlation between productivity growth and hours growth, and 7 of the 20 are statistically significant at the 10% level or less. Over the second sub-sample, 29 of the 31 industries have negative correlation, and 17 of the 29 are statistically significant at the 10% level or less. Thus, the negative correlation has become stronger and more significant in the latter sub-sample. These findings suggest that the overall negative correlation between productivity growth and hours growth in the sample is not driven by the events of the early 1980s alone.

[15] Since the BEID data is from 1970-2000, there is no overlap with the micro data used in Bunn and Ellis (2012b). Greenslade and Parker (2008) conducted an analysis of survey data from 693 UK companies to determine how often they change prices. Approximately 45% of the firms in the sample change price between six months to a year, with about 35% changing prices annually. Moreover, approximately 55% of the companies in the manufacturing sector change prices between six months to a year, and the same goes for about 60% of the companies in the hotels and restaurants sector.

[16] See http://www.tradingeconomics.com/united-kingdom/unemployment-rate.

[17] We do not conduct the SVAR analysis as it is constrained by the short sub-sample periods.

4 Robustness

In this section we examine the robustness of the results to a variety of relevant considerations.

4.1 Utilization corrected TFP

We construct utilization corrected TFP growth at the industry level as follows. We use data on total employees from the New Earnings Survey (NES) and the total hours data in the BEID to construct a measure of hours worked per worker in each industry.[18] The methodology of Basu et al. (2006) allows linking the unobserved utilization in industry i with the observed growth rate of hours per worker ($\tilde{h}_{it}$). The expression for corrected TFP growth in industry i is then given as

$$\Delta TFP_{it}^{\text{corr}} = \Delta TFP_{it} - b_i \Delta \tilde{h}_{it} \tag{4.1}$$

Groth et al. (2006) estimated the coefficients b in (4.1) for six broad industry categories in the BEID. These are (i) mining and oil (industries 2 to 4), $\hat{b} = 4.50$; (ii) manufacturing (industries 5 to 14), $\hat{b} = 1.61$; (iii) utilities (industries 15 to 17), $\hat{b} = 0.11$; (iv) construction, distribution, hotels and restaurants (industries 18 to 21), $\hat{b} = 2.41$; (v) Transport services (industries 22 to 27), $\hat{b} = 2.97$; and (vi) other market services (industries 28, 29, and 34), $\hat{b} = 2.80$. Since the estimates of b at the industry level are not available, we make the assumption that all industries have the same estimated b in each of these six industry groups. For agriculture (industry 1) we make the assumption that the estimated b is the same as that for mining and oil industries. Table 6 (specification 1) presents the results. In line with the benchmark results in Table 5, the unconditional and conditional correlations, and the impact effects remain negative in most industries. The unconditional correlation between utilization corrected TFP growth and hours growth is negative in 28 industries of which 10 are statistically significant at the 5-percent level. The conditional correlations between these variables are negative in 23 industries of which 15 are statistically significant at the 5-percent level. The impact effects are negative in 23 industries of which 15 are statistically significant. The difference occurs in construction and other manufacturing where the impact effect is now zero instead of negative. The conditional correlation and the impact effect changes sign from negative to positive (although remaining statistically insignificant) in the waste treatment services industry. Overall, however, the quantitative conclusions drawn from the benchmark results in Table 2 remain similar.

[18] The annual NES data is from 1969-1999.

4.2 Controlling for the effects of the Aggregate TFP

Following Chang and Hong (2006), we consider a tri-variate SVAR which separately identifies the industry-level and aggregate TFP shocks. This allows us to examine whether the short-run effect on hours to industry-level productivity shocks is not influenced by aggregate TFP. Specifically, the SVAR specification is

$$\begin{bmatrix} \Delta TFP_t^a \\ \Delta TFP_t \\ \Delta h_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) & C^{13}(L) \\ C^{21}(L) & C^{22}(L) & C^{23}(L) \\ C^{31}(L) & C^{32}(L) & C^{33}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^{az} \\ \varepsilon_t^z \\ \varepsilon_t^o \end{bmatrix} \equiv C(L)\varepsilon_t = \sum_{j=0}^{\infty} C_j \varepsilon_{t-j} \tag{4.2}$$

where ΔTFP_t^a is the aggregate TFP and ε_t^{az} is the aggregate TFP shock. The long run identification assumptions used to obtain the aggregate and industry productivity shocks are that (a) the industry productivity shock and the non-productivity shock do not affect aggregate TFP in the long run ($C^{12}(1) = C^{13}(1) = 0$), and (b) the non-productivity shock does not affect the industry TFP in the long run ($C^{23}(1) = 0$). Table 6 (specification 2) presents the results. The conditional correlations in 21 industries is negative (with 20 statistically significant). The positive conditional correlation arises in 10 industries compared to 6 in the bi-variate specification (and 5 statistically significant compared to 2 under the latter). The negative impact effect occurs in 25 industries (with 15 statistically significant, one more than in the bi-variate specification). Thus, overall the employment effects change little indicating that the bi-variate results are robust to the inclusion of aggregate TFP in the SVAR specification.

4.3 Larger SVAR

Research on identifying productivity shocks using long-run restrictions has highlighted some limitations of this approach (see, for example, Faust and Leeper (1997) and Erceg et al. (2005)). One recommendation is to consider a larger VAR specification to reduce biases that may arise due to omitted variables. While our robustness check in section 4.1 was in line with this concern, we use an additional specification where instead of aggregate TFP, we include growth rate of capital (Δk_t) and material inputs (Δm_t), a specification that is similar to the one considered in Chang and Hong

(2006).

$$\begin{bmatrix} \Delta TFP_t \\ \Delta h_t \\ \Delta k_t \\ \Delta m_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) & C^{13}(L) & C^{14}(L) \\ C^{21}(L) & C^{22}(L) & C^{23}(L) & C^{24}(L) \\ C^{31}(L) & C^{32}(L) & C^{33}(L) & C^{34}(L) \\ C^{41}(L) & C^{42}(L) & C^{43}(L) & C^{44}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^{o1} \\ \varepsilon_t^{o2} \\ \varepsilon_t^{o3} \end{bmatrix} \equiv C(L)\varepsilon_t = \sum_{j=0}^{\infty} C_j \varepsilon_{t-j} \quad (4.3)$$

where ε^{ol}, $l = 1, 2, 3$ are the non-technology shocks and the identification restrictions are $C^{12}(1) = C^{13}(1) = C^{14} = 0$.

Table 6 (specification 3) presents the findings for this case. Relative to the benchmark finding in Table 2, the conditional correlations in industries 1 (Agriculture) and 15 (Electric Supply) are now negative and statistically significant.[19] Moreover, the impact effect of industry technology improvement on hours in industries 14 (Other Durable Manufacturing) and 17 (Water Supply) are now negative, and significant in the latter industry. All other findings are similar to those from the benchmark results. The evidence, therefore, suggests that accounting for biases due to omitted variables further strengthen the conclusions drawn from the benchmark results.

4.4 Quadratic detrended hours

Fernald (2007) has pointed out that the quadratic trend may capture the low frequency movements of hours which may be unrelated to the business cycle frequency. Demographic trends may be one source of such low frequency movement in hours (see Francis and Ramey (2009)). These possibilities help explain why in aggregate data VAR, moving from the level specification of hours to first differenced hours or quadratic detrended hours can give opposite conclusions regarding the effects of productivity shocks. In general, specifications using quadratic detrended hours and first differenced hours gives similar results (see Galí and Rabanal (2004)). Although we did not consider the level specification for hours based on the ADF results, it is of interest to check if we obtain results from the quadratic detrended hours that are similar to the benchmark specification. Table 6 (specification 4) reports the results for quadratic detrended hours. These results are based on the trivariate SVAR that controls for the effects of aggregate TFP as in 4.2. We find that both growth and quadratic detrended hours specifications give similar results. That is, short-run hours falls in most industries after positive industry-level productivity shocks.

In the aggregate specifications, the negative correlations and the impact effect on hours are

[19] Table 3 in Appendix.

relatively stronger for the quadratic detrended hours than the growth rate specification of hours (Table 4). In the disaggregated specifications the differences much smaller.[20] One potential reason is that the aggregate quadratic detrended hours specification is better capturing the low frequency movements in hours (such as demographics). As pointed out in Fernald (2007), controlling for the low frequency movement generates larger absolute magnitudes of the negative correlations. Based on this, we think that the effects of low frequency movements in hours may be less prominent at an individual industry level leading to the two specifications giving similar results.

4.5 Markup-adjusted TFP

The TFP in the BEID is constructed under the assumption of perfect competition such that the markup is equal to one. It is likely that the industrial structure implies a positive markup. In such a case, the measured TFP (TFP_t) can deviate from the true TFP (TFP_t^*) as follows:

$$TFP_t = TFP_t^* + (\mu - 1)(\alpha_{m,t}(\Delta m_t - \Delta k_t) + \alpha_{h,t}(\Delta h_t - \Delta k_t)) \tag{4.4}$$

Using average markups of 5% ($\mu = 0.05$) and 10% ($\mu = 0.1$), we can back out two separate measures of markup-adjusted TFP. Chang and Hong (2006) find that the incidence of negative employment effects in the US manufacturing rises when they consider a 10% markup. Table 6 (specification 5) reports the impact effects for the 10% markup case. We do not find any significant difference relative to the benchmark impact effects in Table 2.[21]

5 Conclusion

We investigated the effects of identified productivity shocks on total hours worked in UK industries. Using UK industry data from the Bank of England (BEID) over the period 1970-2000, we find robust evidence that after a positive productivity shock, short-run hours-worked fall in 26 of the 31 industries. We provide an interpretation based on macroeconomic models that can help account for these findings. We highlight an interesting aspect of our findings that in contrast to the US literature, the effects of productivity shocks on hours in the UK are similar at both the aggregate and the industry level. The UK-US differences can be explained by the significantly larger capital

[20] Table 4 in the Appendix.

[21] The findings for the 5% markup case are similar and not reported here.

adjustment costs estimates for the UK industries. Moreover, UK industries with higher investment elasticities (lower capital adjustment costs) have less negative impact effects of hours.

Recent work of Alexopoulos and Cohen (2009a) and Alexopoulos (2011) constructs measures of technological change based on books published in the field of technology, and historical data from the catalogue of the Library of Congress. They examine how employment responds to innovations in these measures. Applying a similar methodology to develop alternative measures of technology in the UK and to examine their effects on hours is a promising direction for research in this area to proceed.

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Table 1: **Diagnostics: Augmented Dickey-Fuller (ADF) Unit Root Tests**

	TFP (LEVEL)					HOURS (LEVEL)				
INDUSTRY	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
1. Agriculture	−2.12	−2.45	−2.48	−3.17	−2.66	−1.47	−0.53	−1.02	−0.63	−0.72
2. Oil & gas	−2.22	−2.56	−2.88	−3.27	−2.36	−2.26	−1.95	−2.18	−2.16	−2.15
3. Coal &other mining	−2.29	−2.02	−2.18	−1.92	−1.78	−1.87	−1.76	−1.25	−1.19	−2.22
4. Manufacturing fuel (ND, mfg)	−2.07	−2.05	−2.93	−2.07	−1.86	−3.44	−2.86	−2.81	−2.50	−1.64
5. Chemicals & pharmaceuticals (ND, mfg)	−2.58	−2.75	−2.52	−2.70	−3.11	−2.84	−2.20	−3.13	−1.89	−2.65
6. Non-metallic mineral products (D, mfg)	−2.51	−2.02	−2.46	−2.30	−2.28	−2.92	−2.08	−1.38	−1.96	−2.29
7. Basic metals & metal goods (D, mfg)	−1.61	−1.70	−1.91	−1.68	−2.54	−1.77	−1.57	−1.43	−0.95	−2.86
8. Mechanical engineering (D, mfg)	−2.27	−2.65	−2.78	−2.58	−2.34	−2.93	−2.31	−2.10	−1.43	−1.91
9. Electrical engineering & electronics (D, mfg)	−2.58	−2.78	−2.54	−2.47	−1.95	−2.90	−2.16	−1.59	−0.58	−1.63
10. Vehicles (D, mfg)	−1.90	−2.00	−1.67	−2.19	−2.87	−1.36	−0.97	−0.99	−0.24	−0.18
11. Food, drink, & tobacco (ND, mfg)	−3.05	−3.29	−3.37	−2.13	−2.36	−0.77	−0.69	−0.58	−0.41	−0.35
12. Textiles, clothing & leather (ND, mfg)	−3.68	−3.73	−3.72	−3.04	−3.17	−3.37	−2.62	−1.89	−2.20	-3.80^{*}
13. Paper, printing & publishing (ND, mfg)	−2.70	−1.90	−2.33	−1.54	−2.87	−2.03	−2.89	−2.22	−1.88	−2.46
14. Other manufacturing (D, mfg)	−1.81	−1.18	−1.32	−1.05	−1.51	−2.71	−1.57	−1.59	−2.04	−1.99
15. Electric supply	−2.82	−2.83	−2.97	−3.43	−3.50	−2.35	−2.65	−3.20	−3.23	−2.41
16. Gas supply	−0.94	−0.92	−1.06	−1.58	−1.36	−1.73	−1.27	−0.32	−0.93	−0.29
17. Water supply	−1.68	−1.79	−2.31	−3.30	−3.02	−0.70	−0.65	−0.09	−0.28	−1.43
18. Construction	-3.95^{**}	−2.34	−1.97	−2.05	−1.99	-3.60^{**}	−2.06	−2.24	−3.04	−2.59
19. Wholesale, vehicle sales & repairs	−2.27	−1.90	−2.02	−2.17	−2.97	-4.39^{***}	−2.19	−2.16	−1.85	−1.73
20. Retailing	-4.24^{***}	−2.81	−2.22	−1.86	−0.91	−1.98	−2.00	−1.71	−2.04	−3.15
21. Hotels & catering	−2.61	−1.80	−1.81	−1.05	−0.28	−2.75	−2.28	−1.87	−1.90	−2.20
22. Rail transport (T)	−1.88	−2.04	−2.20	−3.03	−2.86	−2.32	−1.14	−3.24	−2.89	−2.30
23. Road transport (T)	−1.08	−1.38	−1.01	−0.96	−0.53	−1.70	−1.47	−0.03	−0.34	−0.27
24. Water transport (T)	−1.00	−2.07	−1.20	−1.54	−1.87	−2.96	−3.10	−3.12	-3.57^{*}	−2.30
25. Air transport (T)	−2.22	−2.35	−2.65	−1.78	−2.49	−1.74	−1.13	−0.76	−0.57	−0.67
26. Other transport services (T)	-3.66^{**}	−2.44	−3.01	−2.14	−1.25	−0.47	−0.39	−0.60	−0.46	−0.65
27. Communications	−1.48	−1.19	−0.68	−0.26	−0.15	−1.41	−1.25	−1.90	−1.33	−2.05
28. Finance (S)	−1.82	−1.94	−2.38	−1.87	−2.56	−1.37	−0.78	−1.06	−0.92	−0.97
29. Business services (S)	−1.85	−2.18	−2.12	−2.56	−2.19	−2.27	−1.62	−1.50	−1.75	−1.96
33. Waste treatment	−1.79	−0.74	−1.24	−0.99	−0.33	−2.54	−1.27	−2.02	−1.97	−2.39
34. Miscellaneous services (S)	−2.12	−1.50	−1.46	−1.18	−1.23	−2.18	−2.41	−2.39	−2.38	−3.16

Notes: The ADF test includes a constant and a time trend. The null hypothesis is the presence of a unit root. The 5-percent (**) and 1-percent (***) critical values are −3.54 and −4.20, respectively. 'D' denotes durable, 'ND' denotes non-durable goods industries, 'mfg' denotes manufacturing, 'T' denotes transportation industries, and 'S' denotes services industries. The optimal lag in all industries is between 2 and 4 based on the Schwartz's Information Criterion.

Table 2: **Total Factor Productivity and Hours: Benchmark Results**

INDUSTRY	Corr($\Delta TFP, \Delta h$)	Corr($\Delta TFP, \Delta h \mid z$)	IMPACT EFFECT ON HOURS
1. Agriculture	−0.11 [0.54]	0.25 [0.13]	+
2. Oil & gas	0.24 [0.19]	0.18 [0.35]	+
3. Coal &other mining	−0.29 [0.10]	−0.66 [0.00]	−**
4. Manufacturing fuel (ND, mfg)	−0.64 [0.00]	−0.99 [0.00]	−**
5. Chemicals & pharmaceuticals (ND, mfg)	−0.20 [0.26]	−0.84 [0.00]	−**
6. Non-metallic mineral products (D, mfg)	−0.09 [0.62]	−0.87 [0.00]	−
7. Basic metals & metal goods (D, mfg)	−0.16 [0.38]	−0.88 [0.00]	−**
8. Mechanical engineering (D, mfg)	−0.05 [0.79]	−0.86 [0.00]	−**
9. Electrical engineering & electronics (D, mfg)	0.13 [0.40]	0.98 [0.00]	+
10. Vehicles (D, mfg)	−0.36 [0.04]	−0.99 [0.02]	−**
11. Food, drink, & tobacco (ND, mfg)	−0.59 [0.00]	−0.85 [0.00]	−**
12. Textiles, clothing & leather (ND, mfg)	−0.12 [0.41]	−0.77 [0.00]	−**
13. Paper, printing & publishing (ND, mfg)	−0.05 [0.76]	−0.57 [0.29]	−
14. Other manufacturing (D, mfg)	0.25 [0.18]	0.09 [0.66]	−
15. Electric supply	−0.12 [0.51]	−0.99 [0.00]	−
16. Gas supply	−0.64 [0.00]	−0.99 [0.00]	−**
17. Water supply	−0.28 [0.12]	−0.45 [0.31]	−
18. Construction	−0.08 [0.66]	−0.77 [0.08]	−**
19. Wholesale, vehicle sales & repairs	−0.31 [0.09]	0.29 [0.58]	0
20. Retailing	−0.50 [0.00]	−0.56 [0.00]	−
21. Hotels & catering	−0.39 [0.03]	−0.96 [0.00]	−**
22. Rail transport (T)	−0.86 [0.00]	−0.99 [0.00]	−**
23. Road transport (T)	−0.68 [0.00]	−0.99 [0.00]	−
24. Water transport (T)	−0.47 [0.00]	−0.99 [0.00]	−
25. Air transport (T)	−0.29 [0.11]	−0.82 [0.00]	−
26. Other transport services (T)	−0.30 [0.10]	−0.90 [0.12]	−
27. Communications	−0.23 [0.21]	0.99 [0.00]	−
28. Finance (S)	−0.54 [0.00]	−0.97 [0.00]	−**
29. Business services (S)	−0.36 [0.04]	−0.99 [0.00]	−
33. Waste treatment	−0.17 [0.36]	−0.63 [0.00]	−
34. Miscellaneous services (S)	−0.78 [0.00]	−0.85 [0.02]	−**

Notes: The industry results are based on a bi-variate SVAR: $[\Delta TFP \;\; \Delta h]'$. p-values in square brackets. ** denotes statistical significance at the 5-percent level. 'D' denotes durable, 'ND' denotes non-durable goods industries, 'mfg' denotes manufacturing, 'T' denotes transportation industries, and 'S' denotes services industries. Public sector industries in the BEID (numbered 30, 31, 32) are excluded.

Table 3: **UK versus US: Manufacturing Industries**

US: Chang and Hong (2006)		UK: This paper	
Panel A: CONDITIONAL CORRELATIONS, Corr($\Delta TFP, \Delta h \mid z$)			
I. Non-durables			
Positive	Negative	Positive	Negative
6 (3)	4 (0)	0 (0)	5 (5)
II. Durables			
Positive	Negative	Positive	Negative
9 (6)	1 (1)	1 (0)	5 (5)
Panel B: IMPACT EFFECTS ON HOURS-WORKED			
I. TFP Growth			
Positive	Negative	Positive	Negative
14 (4)	6 (1)	1 (0)	10 (7)
II. Labour Productivity Growth			
Positive	Negative	Positive	Negative
2 (0)	18 (9)	2 (0)	9 (7)

Notes: The numbers represent the number of industries, with statistically significant ones in parenthesis. Total number two-digit manufacturing industries is 20 for the US and 11 for the UK. The US results reported are taken from Chang and Hong (2006) Table 1 for Panel A and, Tables 2 and 3 for Panel B. The number of industries in parenthesis are those with statistically significant response at the 10-percent level for the US (note that Chang and Hong (2006) report only the 10-percent significance level for the impact effects) and 5-percent level for the UK (note that Table 2 and Table 5 in the Appendix reports the p-values).

Table 4: **Aggregate UK Results (1970-2000): Total Factor Productivity and Hours**

Corr(ΔTFP, Δh)	Corr(ΔTFP, $\Delta h \mid \varepsilon^z$)	IMPACT EFFECT ON HOURS
-0.03 [0.54]	-0.78^{*} [0.08]	$-$
Corr(ΔTFP, h^{qd})	Corr(ΔTFP, $h^{qd} \mid \varepsilon^z$)	
-0.47 [0.23]	-0.98^{***} [0.00]	$-^{**}$

Notes: h is four-quarter average of total hours. qd is quadratic detrended. TFP is aggregate total factor productivity denoted as *gtfpagg* in the BEID. p-value in square brackets. *,**, and *** indicate statistical significance at 10, 5, and 1- percent levels, respectively.

Table 5: **Unconditional Correlations between Total Factor Productivity and Hours: Sub-Sample Results**

INDUSTRY	Corr($\Delta TFP, \Delta h$) 1970-1985	Corr($\Delta TFP, \Delta h$) 1985-2000
1. Agriculture	0.06 [0.84]	−0.46 [0.06]
2. Oil & gas	0.28 [0.30]	−0.64 [0.00]
3. Coal &other mining	0.10 [0.71]	−0.39 [0.13]
4. Manufacturing fuel (ND, mfg)	−0.21 [0.44]	−0.85 [0.00]
5. Chemicals & pharmaceuticals (ND, mfg)	0.05 [0.86]	−0.64 [0.00]
6. Non-metallic mineral products (D, mfg)	0.03 [0.91]	−0.20 [0.47]
7. Basic metals & metal goods (D, mfg)	−0.27 [0.32]	0.09 [0.76]
8. Mechanical engineering (D, mfg)	0.03 [0.92]	−0.12 [0.66]
9. Electrical engineering & electronics (D, mfg)	0.33 [0.21]	0.08 [0.78]
10. Vehicles (D, mfg)	−0.28 [0.30]	−0.47 [0.05]
11. Food, drink, & tobacco (ND, mfg)	−0.27 [0.31]	−0.73 [0.00]
12. Textiles, clothing & leather (ND, mfg)	0.16 [0.55]	−0.45 [0.07]
13. Paper, printing & publishing (ND, mfg)	−0.04 [0.89]	−0.05 [0.87]
14. Other manufacturing (D, mfg)	0.49 [0.04]	−0.03 [0.90]
15. Electric supply	−0.15 [0.59]	−0.08 [0.77]
16. Gas supply	−0.80 [0.00]	−0.76 [0.00]
17. Water supply	−0.78 [0.00]	−0.53 [0.02]
18. Construction	0.10 [0.71]	−0.38 [0.14]
19. Wholesale, vehicle sales & repairs	−0.39 [0.13]	−0.08 [0.79]
20. Retailing	−0.59 [0.01]	−0.63 [0.00]
21. Hotels & catering	−0.20 [0.45]	−0.41 [0.11]
22. Rail transport (T)	−0.42 [0.10]	−0.93 [0.00]
23. Road transport (T)	−0.57 [0.01]	−0.71 [0.00]
24. Water transport (T)	−0.05 [0.85]	−0.85 [0.00]
25. Air transport (T)	−0.12 [0.65]	−0.54 [0.02]
26. Other transport services (T)	−0.45 [0.07]	−0.16 [0.57]
27. Communications	−0.25 [0.36]	−0.32 [0.23]
28. Finance (S)	−0.33 [0.21]	−0.78 [0.00]
29. Business services (S)	−0.12 [0.67]	−0.36 [0.16]
33. Waste treatment	0.16 [0.56]	−0.62 [0.00]
34. Miscellaneous services (S)	−0.91 [0.00]	−0.52 [0.03]

Notes: p-values in square brackets. ‘D’ denotes durable, ‘ND’ denotes non-durable goods industries, ‘mfg’ denotes manufacturing, ‘T’ denotes transportation industries, and ‘S’ denotes services industries. Public sector industries in the BEID (numbered 30, 31, 32) are excluded.

Table 6: **A Summary of Robustness Results**

	UNCONDITIONAL CORRELATION		CONDITIONAL CORRELATION		IMPACT EFFECT ON HOURS	
	Positive	Negative	Positive	Negative	Positive/Zero	Negative
1. Utilization corrected TFP						
	3 (0)	28 (13)	8 (1)	23 (18)	8 (0)	23 (15)
2. Controlling for Aggregate TFP						
	3 (0)	28 (13)	10 (8)	21 (12)	6 (0)	25 (15)
3. Larger SVAR						
	3 (0)	28 (13)	7 (6)	24 (23)	6 (0)	25 (15)
4. Quadratic detrended hours						
	2 (0)	29 (10)	6 (1)	25 (13)	7 (1)	24 (11)
5. Markup corrected						
	3 (0)	28 (13)	6 (1)	25 (19)	6 (0)	25 (14)
6. Labour productivity growth						
	2 (1)	29 (18)	4 (0)	27 (16)	4 (0)	27 (19)

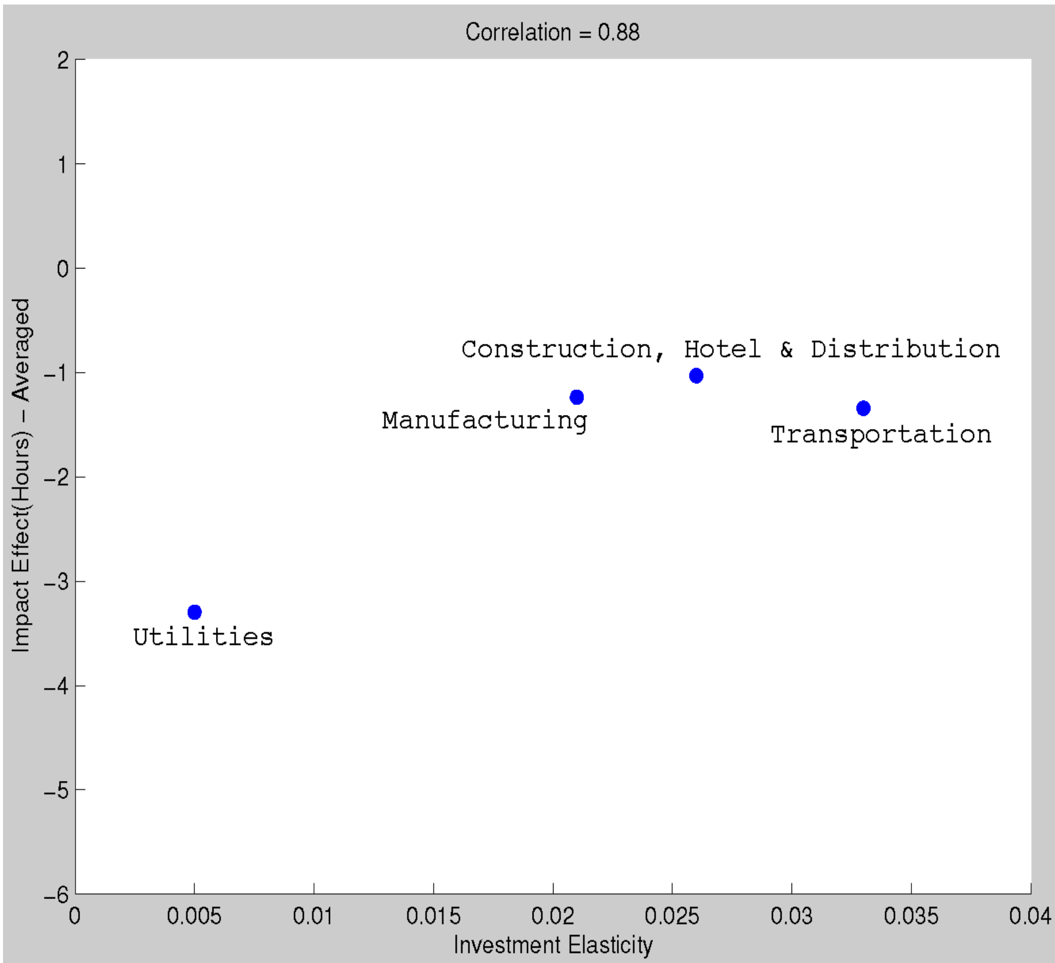
Notes: The unconditional correlation = Corr(ΔX, *hours*) where X denotes a productivity measure considered, either TFP or Labour Productivity, and *hours* denotes either Δh (hours growth) or h^{qd} (quadratic detrended hours). The conditional correlation = Corr(ΔX, *hours*|z), which is conditional on the productivity shock, z. The numbers in parenthesis for the correlations denote the number industries which have a significant correlation at the 10 percent level. The number in parenthesis for the impact effects denote the number of industries which have a significant impact effect at the 5 percent level.

Table 7: **Decomposition of labour productivity growth**

	$\Delta(y-l)$	ΔTFP	$\alpha_m\Delta(m-l)$	$\alpha_k\Delta(k-l)$
1. Agriculture	1.61	0.66	0.42	0.53
2. Oil & gas	4.78	3.10	-1.12	2.52
3. Coal &other mining	6.86	1.28	5.37	0.29
4. Manufacturing fuel (ND, mfg)	1.89	0.27	1.59	0.02
5. Chemicals & pharmaceuticals (ND, mfg)	4.85	1.37	3.11	0.40
6. Non-metallic mineral products (D, mfg)	1.11	-0.06	0.76	0.44
7. Basic metals & metal goods (D, mfg)	3.07	0.51	2.42	0.17
8. Mechanical engineering (D, mfg)	1.58	0.31	1.02	0.28
9. Electrical engineering & electronics (D, mfg)	7.68	3.42	3.65	0.63
10. Vehicles (D, mfg)	3.58	0.96	2.51	0.16
11. Food, drink, & tobacco (ND, mfg)	3.16	0.32	2.55	0.30
12. Textiles, clothing & leather (ND, mfg)	3.52	0.79	2.37	0.37
13. Paper, printing & publishing (ND, mfg)	2.69	0.23	1.96	0.53
14. Other manufacturing (D, mfg)	2.47	0.39	1.77	0.33
15. Electric supply	6.63	1.73	4.46	0.55
16. Gas supply	6.96	2.26	3.94	0.84
17. Water supply	3.83	-1.32	2.37	2.92
18. Construction	2.01	0.02	1.69	0.31
19. Wholesale, vehicle sales & repairs	3.31	0.14	2.24	0.96
20. Retailing	3.70	0.40	2.02	1.34
21. Hotels & catering	1.60	-0.94	2.14	0.50
22. Rail transport (T)	6.20	1.62	4.48	0.26
23. Road transport (T)	3.61	1.05	2.23	0.39
24. Water transport (T)	10.17	0.31	9.48	0.51
25. Air transport (T)	4.17	1.31	2.75	0.19
26. Other transport services (T)	2.51	0.49	1.72	0.40
27. Communications	5.12	1.86	2.07	1.28
28. Finance (S)	4.06	0.36	2.08	1.62
29. Business services (S)	4.50	0.43	2.55	1.54
33. Waste treatment	-0.50	-0.24	-0.92	0.67
34. Miscellaneous services (S)	2.59	-0.15	1.76	1.00

Notes: This decomposition is based on equation (3.1) and averaged over the sample period. 'D' denotes durable, 'ND' denotes non-durable goods industries, 'mfg' denotes manufacturing, 'T' denotes transportation industries, and 'S' denotes services industries. Public sector industries in the BEID (numbered 30, 31, 32) are excluded.

Figure 1: **Investment Elasticity and Impact Effect of Hours to a Positive TFP Shock.**



Notes: The y-axis is the average impact effect on hours of a positive TFP shock that increases industry TFP by 1 percent in the long run. The average impact effect is from the four industry sub-groups of the BEID, namely, (1) Utilities, (2) Manufacturing, (3) Construction, Hotels & Distribution, and (4) Transportation. These groups are ranked in terms of increasing estimates of the elasticity of variable costs with respect to investment (i.e., decreasing capital adjustment costs) given 0.005, 0.021, 0.026, and 0.033, respectively (Groth (2008)).