ANNALES D'ÉCONOMIE ET DE STATISTIQUE. – N° 41/42 — 1996

Job Creation, Technological Innovation and Adjustment Costs: Evidence from a Panel of British Firms

Costas MEGHIR, Annette RYAN, John VAN REENEN*

ABSTRACT. – This paper examines the impact of technological change on net job creation. Innovation (by a company or its rivals) can affect many dimensions of a firm's employment decision and we distinguish between three: changes due to higher output, changes due to shifting factor intensities and changes in the adjustment costs of firms. The parameter estimates from a strucural labour demand model suggest that firms with a higher stock of innovations face lower adjustment costs than less technologically progressive firms. There is no significant capital deepening effect from innovation, nor spillover effects on employment from innovations elsewhere in the firm's industry.

Création d'emploi, innovation technologique et coût d'ajustement : Application au travers d'un échantillon de firmes anglaises

RÉSUMÉ. – Nous examinons l'effet que peut produire l'innovation technologique sur la création d'emploi.

L'innovation faite par une entreprise ou ses concurrentes peut influencer de trois façons différentes leur politique d'embauche. Du fait d'une production plus importante, du fait d'une modification des facteurs d'intensité, du fait des coûts d'ajustements.

Notre modèle structurel de demande de travail montre que plus une entreprise est innovante, plus ses coûts d'ajustements diminuent.

En dehors des industries, les innovations technologiques n'entrainent, ni effet significatif d'augmentation de capital, ni effets sur l'emploi.

* C. MEGHIR, A. RYAN, J. VAN REENEN: Institute for Fiscal Studies, London. We would like to thank John ABOWD, Stephen BOND, Rachel GRIFFITH, Zvi GRILICHES, two anonymous referees and participants in conferences in Paris, London and Washington for many helpful comments. This research is part of a programme of research at the ESRC Centre for Microeconomic Analysis of Fiscal Policy at the Institute for Fiscal Studies.

1 Introduction

One of the main driving forces of employment growth and decline is believed to be technological innovation. Yet little empirical evidence is available to guide policy makers and researchers about the mechanisms by which technical change affects employment. This is particularly surprising given the central role that skill biased technical change is deemed to have had in changing the supply and demand for skills in the United States and United Kingdom over the last 20 years [1]. One of the reasons for the paucity of evidence is data driven. Observable measures of technological change and appropriate panels of micro-economic data on employment are hard to come by. This paper attempts to shed some light on this area by using observable measures of technological innovation combined with firm level panel data.

A feature of our dataset is that innovating firms tend to be more successful than non-innovators in at least two senses. Their financial performance is superior and they tend to have faster employment growth (*see* GEROSKI, MACHIN and VAN REENEN [1993], for the former and VAN REENEN [1994], for the latter). To understand why this is the case it is necessary to distinguish many avenues through which technological change affects employment. Clearly firms may reduce labour inputs for a given output level when new technologies are introduced, but this effect may be balanced by the higher sales arising from the lower costs of production. Furthermore, innovation may affect the adjustment costs that firms face. A firm which has acquired a stock of innovations may find itself more capable of adapting to demand shocks than its more technologically sluggish counterparts. On the other hand, innovation may cause increasing costs of adjustment through the disruptive nature of new technologies.

Identifying costs of adjustment at the firm level is a difficult process for a variety of reasons (*see* HAMERMESH [1993]), but firm level analysis has the major advantage that one is not forced to aggregate over very heterogeneous firms and industries. In particular one can explicitly examine the heterogeneity in adjustment costs across types of firms, as urged by HAMERMESH and PFANN [1994] in their recent survey. We can also test the hypothesis that some type of firms have no adjustment costs.

To pre-empt our conclusions, there is some evidence of adjustment costs for changes in the level of employment from year to year in the sample of 600 manufacturing firms taken as a whole. However, when we distinguish between firms with larger and smaller historical stocks of innovations it appears that highly innovative firms face essentially zero adjustment costs in employment. This is true even after allowing for fixed effects and hence for permanent unobservable differences between firms.

1. *See* BERMAN, BOUND, and GRILICHES [1994] and MACHIN [1995] for some recent evidence on this.

The paper is organised as follows. Section 2 outlines a simple model of employment determination under monopolistic competition and quadratic adjustment costs. Section 3 gives the econometric modelling strategy paying particular attention to the symmetrically normalised method of moments estimator. Section 4 describes the data and section 5 gives the results. Finally section 6 offers some conclusions.

2 Employment Determination and Innovations

In this section we derive the Euler equation for employment of a value maximising firm under the presence of quadratic adjustment costs [2]. We assume that the adjustment costs take the form

$$c(\Delta N_t) = \frac{\delta(G_t)}{2}\left(\frac{(N_t - N_{t-1})^2}{N_{t-1}}\right).$$

so that the costs of adjustment depend on the relative change of employment (N), rather than on the absolute size as per the usual quadratic specification. A key variable of interest is the adjustment cost parameter $\delta_t \equiv \delta(G_t)$, and whether it systematically varies with the firm's knowledge stock (G_t). The value of the firm is given by the discounted sum of current and future profits, i.e.

$$V_t = \Pi_t + E_t \sum_{j=1}^{\infty} \phi_{t+j-1}\Pi_{t+j}, \tag{1}$$

where ϕ_t is the discount factor and Π_t the net profits of the firm defined as

$$\Pi_t = P_t F(N_t, K_t, G_t) - W_t N_t - \frac{\delta_t}{2}\left(\frac{(N_t - N_{t-1})^2}{N_{t-1}}\right). \tag{2}$$

F$(\cdot)$ is the production function, which will depend on labour inputs (N), tangible capital inputs (K) and intangible capital inputs, such as knowledge (G). The expectations operator, E_t, is conditional on information dated t and is taken over future prices and technical change. Monopolistic competition is allowed for in the product market so that the firm's inverse demand curve can be characterised by

$$P_t = B_t Q_t^{-\frac{1}{\eta}}, \tag{3}$$

2. *See* Machin, Manning and Meghir [1993] for an application of the quadratic cost specification in a union bargaining setting. *See* Hamermesh [1993] and Rota [1994] for a discussion of the issues that arise in this area.

where P is price, B an exogenous demand shift parameter, Q the firm's output and η the (constant)-elasticity of product demand. Maximising the value function with respect to employment gives the dynamic first order condition.

$$(4) \qquad W_t = P_t\left(1-\frac{1}{\eta}\right)\left(\frac{\partial F}{\partial N}\right)_t - \delta_t \frac{\Delta N_t}{N_{t-1}} + E_t\left\{\phi_t \delta_{t+1}\frac{\Delta N_{t+1}}{N_t} + \phi_t \frac{\delta_{t+1}}{2}\left(\frac{\Delta N_{t+1}}{N_t}\right)^2\right\}.$$

Notice that technological innovation (which changes the firm's knowledge stock, G_t) can affect employment in several ways. First it will affect the production function either through shifting demand or by altering the mix between capital and labour. Another, more neglected impact of innovation is potentially through its effect on δ, the adjustment cost parameter. In order to obtain an empirically tractable Euler equation we need to adopt some further functional form assumptions. Assume that the production function is Cobb-Douglas with the additional complication that innovation may affect the capital-labour ratio.

$$(5) \qquad F_{t=}G_t^{\gamma} N_t^{\alpha_t} K_t^{1-\alpha_t}$$

$$(6) \qquad \alpha_t = \alpha_0 + \alpha_1 G_t$$

Notice that technology affects production through shifting output via G_t (*see* GRILICHES [1984], for more on incorporating knowledge into the production function). It is also necessary to allow for capital deepening effects which is done by the simple device of allowing the α term to vary with G_t. The stocks are at the beginning of the period and are treated as predetermined for the firm's employment decision. Assume the following form for the adjustment cost parameter.

$$(7) \qquad \delta_t = \delta_0 + \delta_1 G_t$$

The Euler equation becomes

$$(8) \qquad W_t = \alpha_0\left(1-\frac{1}{\eta}\right)\left(\frac{PQ}{N}\right)_t + \alpha_1\left(1-\frac{1}{\eta}\right)\left(\frac{PQ}{N} * G\right)_t - \delta_0 ADJ1_t - \delta_1 ADJ2_t$$

where

$$(9) \qquad ADJ1_t = \frac{\Delta N_t}{N_{t-1}} - E_t\phi_t\left(\frac{\Delta N_{t+1}}{N_t}\right) - E_t\frac{\phi_t}{2}\left(\frac{\Delta N_{t+1}}{N_t}\right)^2$$

and

$$(10) \qquad ADJ2_t = \left(\frac{\Delta N_t}{N_{t-1}} * G_t\right) - E_t\phi_t\left(\frac{\Delta N_{t+1}}{N_t} * G_{t+1}\right) - E_t\frac{\phi_t}{2}\left[\left(\frac{\Delta N_{t+1}}{N_t}\right)^2 * G_{t+1}\right]$$

If there are no adjustment costs then both of the adjustments costs terms, ADJ1 and ADJ2 will have zero coefficients ($\delta_0 = \delta_1 = 0$). If knowledge stocks do not affect adjustment costs then the coefficient on ADJ2 will be zero ($\delta_1 = 0$). If adjustment costs are lower for innovative firms we expect $\delta_1 < 0$.

3 The Econometric Specification

The stochastic specification of our model is induced by the discrepancy between $ADJ1_t$ and $ADJ2_t$ (which depend on the expected growth rate of employment and on the conditional variance of employment growth) with its measured value evaluated at the realised outcomes. The stochastic form of the equation to be estimated is

$$(11) \quad W_t = \beta_1\left(\frac{PQ}{N}\right)_t + \beta_2\left(\frac{PQ}{N} * G\right)_t + \beta_3 ADJ1_t + \beta_4 ADJ2_t + u_{t+1}$$

where $\beta_1 = \alpha_0\left(1 - \frac{1}{\eta}\right)$, $\beta_2 = \alpha_1\left(1 - \frac{1}{\eta}\right)$, $\beta_3 = -\delta_0$ and $\beta_4 = -\delta_1$. Under the hypothesis of rational expectations this expectational error u_{t+1} is uncorrelated with all variables in the firm's information set in period t. In other words the only endogenous variables in equation (11) are $ADJ1_t$ and $ADJ2_t$ because of their dependence on employment in period t+1 (N_{t+1}). There are a number of reasons though why this may not be true in practice. First, the observation period may represent an aggregation over decision periods. Second, there may be lags in the implementation of the decisions. For these reasons we estimate the model in first differences using instrumental variables lagged at least two periods. This allows the error term in the original levels equation to be an MA(1) error.

The model is identified by the exclusion of dynamic terms as implied by the assumed structure of the theoretical model. Nevertheless, it remains an issue whether the past values of employment and innovations can predict the changes of the variables in (11). If there are adjustment costs we can expect past employment levels to be correlated with $\Delta ADJ1_t$ and $\Delta ADJ2_t$ simply because employment is persistent. Secondly, past innovations are correlated with the interactions of the knowledge stock with productivity growth and with $\Delta ADJ2_t$ because the knowledge stock is a function of all past innovations.

It is interesting to see what would identify the model (including the coefficients on the adjustment cost terms) under the null hypothesis that adjustment costs are zero. In this case identification is harder since adjustment costs can not be invoked to explain the persistence of employment. Nevertheless it is reasonable to believe that there are adjustment costs to the capital stock. Hence we also use past values of the capital stock which is persistent and likely to generate persistence in the level of employment. Thus lagged employment, lagged capital and lagged innovations identify our model.

Conventionally the model is re-normalised so that it takes the form of an AR(2) in employment with an extra wage term and average labour productivity. This is inappropriate when there are no adjustment costs since the re-normalisation involves dividing by a parameter that may be zero. We chose to estimate the model in a way that the resulting coefficients are invariant to the choice of dependent variable. The implicit normalisation used is $\sqrt{1+\sum \beta_i^2}$ as suggested by HILLIER [1990] and further developed in the context of GMM estimators by ALONSO-BORREGO and ARELLANO [1994]. Symmetrically normalised GMM (or SN-GMM) has several advantages in our context. Many recent papers have pointed to the problems of the finite sample bias of IV estimators when the instruments are poorly correlated with the endogenous variables (for example, BEKKER [1994] or BOUND, JAEGER and BAKER [1993]). In the GMM context there are a large number of overidentification restrictions, but they may have poor predictive power. Under these circumstances, standard GMM will provide results that are biased in the same direction as OLS. SN-GMM, by contrast, does not have this undesirable feature. The estimator we use is thus invariant to the choice of left hand side variable. Moreover a direct test of the null hypothesis that there are no adjustment costs is simple (the coefficients on the adjustment cost terms are both zero). The adjustment cost parameter can be recovered and compared across firms with different innovation stocks. The computed standard errors allow for both serial correlation and heteroskedasticity. A full description of the estimation technique is given in the Appendix.

4 Data

The dataset used in this study is a rich and unique combination of several sources (*see* Data Appendix for a full description). The primary database is a panel of manufacturing firms listed on the London Stock Exchange for at least five years between 1976 and 1982. There are 600 firms in all employing a total of 3.11 million workers in 1980 (48% of all UK manufacturing employment). To this we matched innovation count data drawn from the Science Policy Research Unit's Innovation Database (SPRU). The SPRU data contains 4378 innovations commercialised in Britain since World War

II. The data collection was done in three waves (1970, 1980 and 1983). Over 400 experts from science, industry and academia were asked to identify the *'successful commercial introduction of new or improved products and processes introduced in Britain between 1945 and 1983'*. The individuals were chosen to reflect their areas of expertise in different industrial branches. After collecting details of the innovations the SPRU team contacted the firms who had first commercialised them for more information on the company's characteristics and the timing of the innovation.

The SPRU dataset has been used extensively by economic researchers, but mainly at the industry level. Econometric work by GEROSKI [1991] and STERLACHINNI [1989] has established a statistically significant link between the numbers of innovations used in an industry and productivity growth. MACHIN [1995] finds that the lagged number of SPRU innovations used in 16 manufacturing industries is a significant predictor of the growth in the employment share of non-manual workers between 1980-85. Matching the innovations to company accounts information allowed the construction of a count of the number of innovations a firm commercialised in a given year ($INNOV$) , the number of innovations produced in its main industry (IPI) and the number of innovations used (IUI) in its main industry. These latter industry variables are taken from the entire SPRU population and are designed to reflect spillovers from knowledge generated by other firms in the industry. In all, about a third of the relevant SPRU population are contained in our dataset. The losses are mainly due to the absence of smaller non-listed companies from our data, who accounted for a greater number of SPRU innovations than their size would suggest. The innovations of these small firms are included in the industry innovation totals. Since it is possible to track a firm's innovation history back to 1945 it is possible to allow a much longer lag structure, even though adequate firm level data on employment is available to us only from 1976.

What are the advantages of using the innovations data and is it appropriate to examine the question at hand? First, note that unlike patents SPRU innovations are relatively rare. The majority of firms do not innovate and of those who do most innovate only once or twice. Essentially this means that we are capturing major technological shifts. Patents are more common and extremely heterogeneous in value: there are many duds and a few bonanzas (*see* PAKES [1986], for example). To draw this contrast out U.S. patents taken out by UK firms were also matched to the dataset. The two variables are reasonably correlated and share a similar distribution across firms [3]. Appendix Table 2 illustrates that patents are far more common. There are a total of 222 innovations by the firms between 1976-82 compared to over 4000 patents. It is therefore unsurprising that profitability regressions on this data [4] suggest that the return to an average SPRU innovation is far higher than the return to a typical patent.

3. The correlation between patents and innovations (0.44) is far from perfect. This is because patents are well known to be a poor mode of protecting knowledge in many sectors compared to secrecy, lead times, retention of key personnel, etc. (*see* LEVIN *et al.* [1987]).

Second, innovations counts have advantages over other, more conventional measures of technology. Total factor productivity suffers from the fact that it is a residual and contains a variety of unknown biases. R&D expenditures are problematic because many firms report no formal R&D and yet still manage to innovate [5]. This is because many smaller firms are involved in informal search for new technologies without having R&D labs.

"Knowledge stocks" were constructed by using depreciated lags of past innovations

$$G_t = INNOV_t + (1-\lambda)G_{t-1}$$

and at the industry level

$$G_t^{user} = IUI_t + (1-\lambda)G_{t-1}^{user}$$

$$G_t^{prod} = IPI_t + (1-\lambda)G_{t-1}^{prod}$$

The stock of innovations used in the industry (G_t^{user}) is expected to be a component of the firm's knowledge due to spillovers, but it seems less likely that innovations produced in the industry (G_t^{prod}) but used in another, should have an effect.

The choice of λ is arbitrary, but experiments were conducted with a variety of depreciation rates [6]. In any event, the exact choice of λ did not seem to qualitatively affect the results and a value of 0.3 is used for the depreciation of innovation and patent stocks as in COCKBURN and GRILICHES [1988].

The employment variable used is total UK employment (firms did not have to disclose this after 1982). Productivity is the ratio of sales to employment deflated by an aggregate price index. Ideally we would like a measure of value added but this is not easily available at the firm level. Capital (which is used as an instrument) is simply the sum of the historic costs of fixed assets deflated by an investment price index. This is obviously a crude measure as the valuation of capital will reflect many firm specific factors including innovation which will alter the implied value of different capital vintages. Rather than making the usual assumption of a constant discount factor we used real interest rates (in particular the annualised yield on Treasury Bills) to construct a time varying measure of ϕ_t. The wage is derived by dividing total UK remuneration by UK employment and deflating by an aggregate

---

4. GEROSKI, MACHIN and VAN REENEN [1993] calculated that the average long-run value of a SPRU innovation was about $3m at 1985 prices. SHANKERMAN and PAKES [1986] using option values on British patents calculate a median value of $1,861.

5. This is a particular problem in the UK over this period as accounting regulations governing R&D disclosure were very weak until 1989.

6. In principle λ can be identified using non-linear estimation techniques.

price index [7]. An important problem with this wage measure is that there is no information on skill composition as this is simply unavailable at the firm level [8]. Naturally this raises the issue of how much of the variation in the wage is due to differences in the price of labour rather than differences in the skill mix over time and across firms. Since the skill mix changes only slowly over time, much of this will be swept out by taking first differences. There is still likely to be some useful firm variation over time as wage setting institutions were undergoing very large changes over this period which impacted differentially across companies (the proportion of workers who were members of trade unions rose from 51.0% in 1976 to a historical high of 53.1% in 1979 before beginning a decline to 47.8% by 1982).

TABLE 4.1

Descriptive Statistics

		All		Innovators[a]		Non-innovators	
Variable		**Mean**	**Std. Dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
wage	*(£1000's)*	6.522	1.476	7.086	1.227	6.350	1.503
productivity	*(£1000's)*	46.319	58.185	58.109	96.233	42.742	39.406
productivity $*$G	*(£1000's)*	12.828	70.854	53.313	139.112	0.545	5.770
ADJ1		0.010	0.716	0.010	0.522	0.010	0.766
ADJ2		0.004	0.277	0.145	0.573	0.001	0.023
employment	*(1000's)*	8.057	20.922	19.439	31.070	4.604	15.063
$\triangle$log(employment)		-0.025	0.155	-0.035	0.164	-0.023	0.153
Innovations							
produced in firm		0.053	0.327	0.210	0.641	0.005	0.071
produced in industry		9.646	14.811	12.435	16.265	8.800	14.238
used in industry		3.988	4.898	4.723	5.124	3.765	4.806
firm patents		1.223	8.899	4.758	17.963	0.151	0.735
Knowledge stocks							
G		0.216	0.898	0.890	1.688	0.011	0.097
G^{prod}		33.677	48.415	43.998	52.944	30.545	46.522
G^{user}		14.061	15.095	16.816	15.472	13.226	14.883
market share		0.028	0.070	0.068	0.114	0.016	0.042
capital	*(£1,000,000's)*	40.017	166.605	119.190	322.654	15.997	46.543
firms		600		139		461	
observations		2045		476		1569	

Notes: All variables in 1985 prices. Number of observations refers to estimating sample .

[a] *A firm is designated as an innovator if it produced an innovation in any year between 1945 and 1976.*

Means and standard deviations for the estimating sample and for innovators and non-innovators are contained in Table 4.1. Data sources are listed in Table 1 in the Data Appendix. Just under 25% of our sample have innovated at least once and these firms tend to have higher employment than their less innovative counterparts. They also have higher wages, market

7. Obviously one would like a better measure of the wage, taking hours and skill composition into account, but this is simply not available at the company level in the UK.
8. There is also no information on hours. These problems are shared by almost all longitudinal company level analyses.

shares and capital stocks. Unsurprisingly they tend to be located in industries with larger numbers of innovations and R&D intensities.

One interesting feature of the data is that innovating firms tend to have a profitability advantage over non-innovators. This profitability difference appears particularly pronounced the recessionary period of the early 1980s and has led some commentators to argue that what innovation buys a firm is greater flexibility (GEROSKI, MACHIN and VAN REENEN [1993]). One aspect of this flexibility could be the ability to move to equilibrium levels of employment faster than non-innovators, and this is the issue that we are focusing on in this paper.

TABLE 4.2

Mean of Standard Deviations Within Firms Over Entire Sample Period

	All	Innovators[a]			Non-innovators		
Standard Deviation		All	ukemp <5000	ukemp >5000	All	ukemp <5000	ukemp >5000
logarithms							
employment	.163	.172	.197	.145	.160	.162	.143
wage	.081	.078	.074	.083	.082	.082	.081
output	.251	.258	.274	.240	.248	.250	.237
productivity	.130	.133	.128	.139	.129	.128	.134
differenced logarithms							
employment	.121	.125	.144	.105	.120	.122	.103
wage	.071	.064	.064	.065	.073	.073	.070
output	.137	.131	.157	.102	.139	.144	.101
productivity	.140	.140	.141	.139	.139	.140	.136
firms	600	139	68	71	461	403	58
observations	3845	893	469	424	2952	2608	344

Notes: All variables in 1985 prices. Number of observations refers to entire sample.

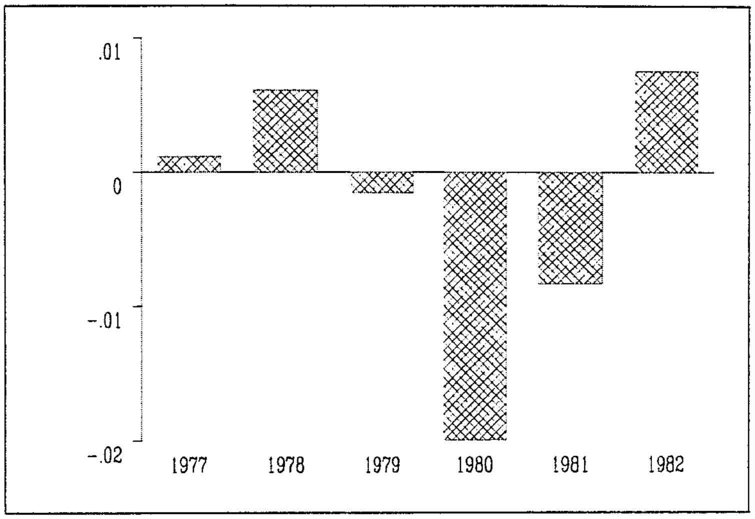
[a] *A firm is designated as an innovator if it produced an innovation in any year between 1945 and 1976.*

As a simple descriptive exercise the within firm standard deviations of employment levels and growth were calculated and are contained in Table 4.2. A firm is designated an innovator if it has a positive knowledge stock in its first year of inclusion in the sample [9]. Innovators tended to have a greater variance in employment and employment growth than non-innovators which is consistent with the idea that innovators face lower adjustment costs. This difference was not simply because they were larger – even amongst firms with below average employment, the employment variance of innovators tended to be higher. Neither did this seem simply due to the greater variability of output shocks in the markets where innovative firms operate. The standard deviation of output growth was greater amongst non-innovative than innovative firms (0.139 versus 0.131). However, for

9. There were ten firms who were pre-sample "non-innovators" who did produce an innovation over the sample period. The discussion below is not substantially affected if we redefine the "innovators" to include the within sample innovators.

FIGURE 1

Difference in Means of Employment Growth Rates (Innovating vs. Non-Innovating Firms)



Note:

$$Difference = \frac{1}{F^I}\sum_{FI}\left(\Delta \log N^I\right) - \frac{1}{F^{NI}}\sum_{FNI}\left(\Delta \log N^{NI}\right);$$

where N^I= employment of innovating firms; N^{NI} = employment of non-innovating firms; F^I = number of pre-sample innovating firms; F^{NI} = number of pre-sample non-innovating firms.

smaller firms, it did appear that there was more variability in output growth amongst non-innovators than innovators. Clearly, it is important to control for output when examining employment adjustment costs and this is what the econometric framework attempts to do. Before examining the results from this it is interesting to note that firms with higher stocks of innovation grew a lot faster during upswings of the cycle (1976-1978 and 1982) and shrank a lot faster during downswings (1979-81). This is drawn out in Figure 1 which contains the (log) employment growth differential between innovative and non-innovative firms over our sample period.

5 Results

The main results are contained in Table 5.1. All models have been estimated in first differences to eliminate fixed effects. Column (I) simply reports the static OLS equation. Columns (II)-(V) show SN-MM estimates for a common instrument set. The instruments used are employment, capital,

TABLE 5.1

Adjustment Costs and Innovation

Wages	**(I)** *OLS*	**(II)**	**(III)**	**(IV)** *SN-MM[a]*	**(V)**
$\frac{Q}{N}_t$	0.0021	0.0209	0.0179	0.0172	0.0177
	0.0016	*0.0069*	*0.0069*	*0.0084*	*0.0080*
$\left(\frac{Q}{N}*G\right)_t$	-	-	-	-0.0004	-
				0.0007	
$ADJ1_t$	-	-	-0.0960	-0.1342	-0.1323
			0.0694	*0.0785*	*0.0789*
$ADJ2_t$	-	-	-	0.1162	0.1213
				0.0443	*0.0496*
constant	0.2525	0.2552	0.2545	0.2508	0.2501
	0.0218	*0.0265*	*0.0263*	*0.0264*	*0.0267*
Year=1980	0.0356	0.0013	0.0093	0.0181	0.0169
	0.0280	*0.0393*	*0.0370*	*0.0378*	*0.0379*
Year=1981	-0.0427	0.0628	0.0554	0.0560	0.0602
	0.0298	*0.0504*	*0.0494*	*0.0563*	*0.0544*
Year=1982	-0.0712	-0.0763	-0.0916	-0.0932	-0.0918
	0.0314	*0.0330*	*0.0353*	*0.0360*	*0.0360*
Sargan	-	29.65	25.02	18.78	21.11
df	-	21	20	18	19
p-value	-	0.099	0.201	0.406	0.331
Auto-correlation [b]					
Second order	-0.169	-0.157	-0.202	-0.210	-0.207
Third order	-0.093	0.120	0.098	0.098	0.104
Test of sc(2) [c]	-1.635	-1.881	-1.737	-1.680	-1.673

Notes: [a] *Estimation is symmetrically normalized method of moments for 600 firms and 2045 observations, after taking first differences to eliminate fixed effects.*
[b] *Second order auto-correlation = cor($\Delta u_{t+1} \Delta u_{t-1}$).*
Third order autocorrelation = cor($\Delta u_{t+1} \Delta u_{t-2}$).
[c] *sc(2) is a test of second order auto-correlation with 575 degrees of freedom, following ARELLANO and BOND [1991].*

and innovations – all lagged two and three periods – and the first lag of employment growth ($\triangle N_{t-1}/N_{t-2}$).

In column (I) productivity enters positively with a small coefficient. There is some evidence of downwards bias from endogeneity, however. Column (II) implements the static IV model with no adjustment costs. The coefficient rises to 0.021 and is significant at conventional levels. There is a suggestion of imperfect competition as the parameter is too small to be consistent with a plausible measure of an output-employment elasticity. Column (III) then includes the adjustment cost term. This enters with its expected sign (recall that $\beta_3 = -\delta_0$ in equation (11)), but is not significant. Column (IV) implements our general model (11) which allows for the effects of innovation on adjustment costs and factor shares. Although the negative sign of the interaction with output suggests that innovation may be capital-deepening, the coefficient is far from statistical significance. By contrast, there is strong evidence that adjustment costs are significantly lower for firms with higher knowledge stocks. Firms which have very high knowledge stocks essentially face zero costs of adjustment. The final column (V) drops the insignificant interaction with output. To draw the results out, Table 5.2 calculates the value of the adjustment costs parameter (δ) at different quintiles of G, the innovation stock, for positive G. Recall that G is a weighted sum of all past innovations with an overall mean of 0.216.

TABLE 5.2

Adjustment Cost Parameter Estimates by Percentiles of G for G>0

Percentile	0.2	0.4	0.6	0.8
G	0.012	0.099	0.504	1.082
δ	0.131	0.120	0.071	0.001
number of firms	28	28	28	28

The Sargan test of the overidentifying restrctions fails to reject the nul hypothesis of instrument validity in all of the above specifications, but there does appear some minor evidence of second order serial correlation (even though it is insignificant at even the 10% level in our preferred specification). Consequently we used only instruments lagged at least three periods which allows for an MA(1) process in the error term in the levels specification of (11). Examination of the residual correlation matrix suggested that there was no role for higher order autocorrelation and so these long dated instruments should be valid as the Sargan statistic implies.

The proxy used for the knowledge stock of the firm is based only on the firms' own innovation history. A priori it is likely that the stocks of innovations used in the firm's principal industry may also have an effect on employment through the diffusion process. One experiment is presented in column (I) of Table 5.3 which allows an additional interaction of productivity and industry innovation stock. Although the sign of the variable implies capital-deepening (much as the firm level measure did), it is very imprecisely estimated. The adjustment cost terms with the industry innovations stock variable were also insignificant, with a coefficient estimate of -0.0005 and standard error of 0.0005. This result is somewhat reassuring as it suggests that the lower adjustment costs of innovating firms is not simply reflecting some technological feature of the industry. Finally, we also used the stock of innovations produced in the firms' industry, but these were also insignificant at conventional levels.

One should not draw the conclusion that spillovers do not exist. Rather, spillovers may be more important for R&D conducted before it is embodied in a particular product or process.

In columns (II)-(IV) some further robustness checks are presented. Instead of allowing the discount factor to vary with the aggregate interest rate, column (II) assumes a constant interest rate of 5%. Again, our estimates are insensitive to this assumption. Innovations are rare events and it may be that lags are poor predictors of whether a firm will innovate or not. An attractive alternative is to use patents as external instruments for the knowledge stock. Patents can be interpreted as a proxy for R&D, with which they are known to be highly correlated. In column (III) we replace innovations with patents in the instrument set. The primary conclusion that

TABLE 5.3

Adjustment Costs and Innovation Robustness Checks

Wages	**(I)**	**(II)**	**(III)**	**(IV)**
	Industry Spillovers	$\phi = \frac{1}{1.1}$	*Patents as IV*	*Alternative depreciation rate*[a]
$\frac{Q}{N}t$	0.0230	0.0175	0.0039	0.0170
	0.0084	*0.0085*	*0.0068*	*0.0080*
$(\frac{Q}{N}{*}G)_t$	-0.0001	-0.0003	-0.0004	-0.0002
	0.0006	*0.0007*	*0.0058*	*0.0007*
ADJ1$_t$	-0.1230	-0.1330	-0.1553	-0.1345
	0.0776	*0.0774*	*0.0840*	*0.0781*
ADJ2$_t$	0.1148	0.1240	0.0931	0.0524
	0.0484	*0.0474*	*0.0365*	*0.0179*
$(\frac{Q}{N}{*}G^{user})_t$	-0.0005	-	-	-
	0.0005			
constant	0.2558	0.2497	0.2508	0.2489
	0.0256	*0.0264*	*0.0240*	*0.0265*
Year=1980	0.0179	0.0184	0.0410	0.0200
	0.0345	*0.0382*	*0.0302*	*0.0374*
Year=1981	0.0485	0.0571	-0.0180	0.0571
	0.0556	*0.0564*	*0.0474*	*0.0551*
Year=1982	-0.1294	-0.0910	-0.0953	-0.0908
	0.0502	*0.0355*	*0.0356*	*0.0360*
Sargan	18.45	18.81	28.03	19.82
df	17	18	18	18
p-value	0.361	0.404	0.062	0.343
Autocorrelation[b]				
Second order	-0.256	-0.203	-0.225	-0.211
Third order	0.018	0.099	-0.031	-0.094
Test of sc(2)[c]	-1.848	-1.698	-1.780	-1.660

Notes: Estimation is symmetrically normalized method of moments for 600 firms and 2045 observations, after taking first differences to eliminate fixed effects.

[a] *We allow λ = 0.15.*

[b] *Second order autocorrelation = cor($\Delta u_{t+1}\Delta u_{t-1}$).*
Third order autocorrelation = cor($\Delta u_{t+1}\Delta u_{t-2}$).

[c] *sc(2) is a test of second order autocorrelation with 575 degrees of freedom, following ARELLANO and BOND [1991].*

adjustment costs are significantly lower for innovating firms appears robust to this instrumentation strategy, although the coefficient on productivity does fall somewhat. Finally, we experimented with different depreciation rates on the knowledge stock variable. Column (IV) shows one such experiment where we allow a slower depreciation rate ($\lambda = 0.15$). The results appear to be qualitatively robust to this experiment, although there is a smaller coefficient on ADJ2 reflecting the higher mean of the knowledge stock variable.

One additional concern is that the highly innovative firms have lower adjustment costs for reasons other than their high knowledge stocks. For example, Table 4.1 shows that firms who innovate have far higher market shares than those who do not. As a simple test the adjustment cost parameter was allowed to vary with both innovation stocks and market share. The market share interaction took a coefficient estimate of 0.108 with a standard error of 0.060. The innovation interaction remained negative and significant -0.033 with a standard error of 0.016. This suggests that larger firms actually have higher adjustment costs. Thus it seems highly unlikely that the innovations variable is merely picking up a firm size or market structure effect (*see* BLUNDELL, GRIFFITH and VAN REENEN [1995], for a deeper analysis of the relationship between innovation and market share).

6 Conclusions

In this paper we have examined the impact of technological innovation on adjustment costs for employment. An Euler equation for employment was derived under the assumption of quadratic adjustment costs. The production function and adjustment cost parameters were allowed to depend on the firms' stocks of knowledge as proxied by past innovations.

It was found that technological innovation is associated with higher employment, but this raw correlation may simply be due to the fact that large firms have higher innovative activity. We control for this by first differencing to remove permanent effects. According to the main results, adjustment costs in employment appear significantly lower for firms with larger stocks of past innovations. In this sense, innovating firms are more "flexible" than non-innovators. This suggests that firms may innovate not simply to increase production, but also to insure themselves against shocks. When faced with these shocks, innovative firms can move to their equilibrium levels of employment more rapidly than non-innovators. Thus it may appear that during recessions technological competency is associated with job loss, but the flipside of this is that during booms more jobs are created by technologically dynamic firms.

One problem with this analysis is that we have no information on the skill mix within firms. Thus, there is a possibility that some of the observed variation in wages is driven not by changes in the price of labour, but rather by changes in the quality mix of workers within firms. The choice of estimation method, namely the fact we use first differences, attenuates this problem. Nevertheless, a challenge for future research is to examine ways in which other data sources could be exploited to deal with the problem of aggregating across differentially skilled employees. This is an avenue that we are currently exploring.

• The estimator

Equation (11) can be written compactly as

$$\Delta y_{it} = \beta' \Delta x_{it} + \Delta u_{it}$$

where Δ is the first difference operator. We assume that $E(\Delta u_{it}|z_{it}) = 0$ for an appropriate choice of instruments z_{it} (see main text for a discussion of the choice of instruments). Define by ΔY, ΔX and Z the matrix containing the data on all individuals for all time periods for the left hand side variables, the right hand side variables and the instruments respectively. The parameter vector β can now be estimated by method of moments estimator which here is the standard linear IV estimator. (*see* HOLTZ-EAKIN, NEWEY and ROSEN [1988] or ARELLANO and BOND [1991])

$$\beta_{GMM} = (\Delta X' M \Delta X)^{-1} \Delta X' M \Delta Y$$

where $M = (ZA_N Z')$, $\Delta Y = (\Delta Y_1^{'}, ..., \Delta Y_N^{'})$, $\Delta X = (\Delta X_1^{'}, ..., \Delta X_N^{'})$, $Z = (Z_1', ..., Z_N')$ and $A_N = (Z'Z)^{-1}$.

Following ALONSO-BORREGO and ARELLANO [1994] we instead apply a LIML type estimator (*see* THEIL [1971]) which has the attractive properties that i) it is not biased toward OLS in small samples when the instruments are not very informative about the endogenous variables and ii) it is invariant to which variable is chosen to have its coefficient normalised to one. The estimator minimises

$$C = \frac{\Delta u' M \Delta u}{1 + \beta' \beta}$$

and is computed by

$$\beta_{SNM} = (\Delta X' M \Delta X - \tilde{\lambda})^{-1} \Delta X' M \Delta y$$

where $\tilde{\lambda} = min\ eigen(W'MW)$ and $W = (\Delta y, \Delta X)$. and where all the variables W are endogenous. In the just identified case $\tilde{\lambda} = 0$ and $\beta_{SNM} = \beta_{GMM}$. More generally, $plim_{N \to \infty} \tilde{\lambda}/N = 0$ if the overidentifying restrictions are valid. Hence the asymptotic properties of this estimator are identical to the properties of the more standard IV estimator.

• Data

The database combines several company datasets together with industry and aggregate information. The firm sources include:

(i) **Firm accounts** from the DATASTREAM on-line service and EXSTAT records of company accounts between 1968 and 1986. These are basically populations of all firms listed on the London Stock Exchange. Firms who had fewer than five continuous time series observations, whose principal operating industry (defined by sales) was outside manufacturing, or who were involved in large scale merger activity were removed from the sample.

(ii) **Science Policy Research Unit's innovations database**. This consists of over 4300 major innovations defined as "the successful commercial introduction of new or improved products, processes and materials introduced in Britain" between 1945 and 1983. Each innovation has a short description and the year of the first commercial introduction. There is a sharp fall in 1983 which appears to be due to the fact that the survey was conducted mid-year (there were similar single year drops in the previous two waves in 1970 and 1980). Consequently 1983 was dropped. There was no systematic evidence of a tail off towards the end of the sample period due to expert inability to predict whether a given innovation was important or not. There is, however, some evidence of imperfect recall, so data pre 1960 is less reliable than after this date.

The aggregate innovations data displays discernable peaks and troughs at roughly five year intervals. The distribution of innovations across industries appears broadly stable over time with the bulk concentrated in four two digit industries - mechanical engineering, electrical engineering, vehicles and chemicals. Nevertheless there is a far larger amount of variation within the 44 industries in innovative activity than there is between industries.

Innovators are identified by 'innovating unit' which we parented using Dun and Bradstreet's *Who Owns Whom* from various years. When matched to company accounts about 30% of all the manufacturing innovations in the SPRU dataset over 1976-82 were captured. For example, in 1978 there were 172 SPRU innovations and 50 of these are our final dataset. The reminder mainly accrue to smaller firms who are not on the Stock Exchange. Examples of innovations include turbomolecular pumps, a lightweight rotary drill for masonry, an aphicide for pest control, Interferon, solar glass windows, photochromatic glass and superplastic furniture.

The data has been used extensively by UK researchers and a full bibliography is contained in GEROSKI [1995]. The data itself is lodged at the ESRC Data Archive at the University of Essex and is described in great length in Robson and TOWNSEND [1984]

(iii) **Patents** granted to UK firms by the US patents office between 1969 and 1988. The decision to use US patents rather than UK patents was in order to screen out the numerous very low value patents taken out each year. These were also parented and matched in the same way as the innovations data using the company name. This task was accomplished by Chris Walters from the London Business School.

After cleaning we were left with 600 firms between 1976 and 1982. The balance of the panel was as follows: 25 firms with 5 years of data, 305 with 6 years of data and 270 with 7 years of data. Details of the means, standard deviation and sources of all variables are in Appendix Table 1.

Wages. Total remuneration divided by total employment. Until July 1982 companies were required to disclose the number of UK employees and remuneration. As of this date, the requirement was for group totals only (which includes overseas employment).

Employment. Total number of UK employees.

Capital. Historic cost of land/building, plant/machinery and other fixed assets deflated by an investment goods price index.

Interest Rates. (Annualised) 9 month Treasury bond yield. Taken from Economic Trends and Statistics (ETAS).

Price Index. Taken from aggregate GDP deflator from ETAS

TABLE 1

Sources and Definitions

Mnemonic	Definition	Source
wages	firm average wage	DS214, XSC16
employment	firm employment in UK	DS216, XSC15
productivity	real sales/employment	DS104,XSC15,DS216,XSC15
INNOVS	no. of firm innovations	SPRU
patents	no. of patents granted to firm in U.S	US Patent Office
capital	log firm capital - historic value	DS327,328,329
IPI	no. of industry innovations produced	SPRU
IUI	no. of industry innovations produced	SPRU
Number of firms	600	

Notes: All variables in 1985 prices.
DS=Datastream, XSC=Exstat, SPRU=Science Policy Research Unit.

TABLE 2

Distribution of innovations and patents by firm, 1976-82

band width	firms innovating	no. of innovations	firms patenting	number of patents
0	526	0	406	0
1	35	35	58	58
2	17	34	24	48
3	5	15	11	33
4	2	8	17	68
5	3	15	7	35
6-10	8	58	25	196
11-50	4	57	27	645
51+	0	0	25	3610[a]
total	600	222	600	4693

Notes: column (1) refers to number of innovations or patents per firm in the sample
column (2) refers to the number of firms who produced a total number of innovations in the band range
column (3) refers to the total number of innovations in the band range
column (4) refers to the number of firms who produced a total number of patents in the band range
column (5) refers to the total number of patents in the band range
[a] the patents number here is dominated by one firm (Imperial Chemicals Industries) which patents 1396 times ICI is also the largest innovator, having a total of 19 innovations between 1976-82

References

ALONSO-BORREGO, ARELLANO, M. (1994). – “Symmetrically Normalised Instrumental Variable Estimation using Panel Data”, *mimeo*, CEMFI.

ARELLANO, M., BOND, S. (1991). – “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations”, *Review of Economic Studies*, 58, pp. 277-98.

BLUNDELL, R., GRIFFITH, R., VAN REENEN, J. (1995). – “Dynamic Count Data Models of Technological Innovation”, *Economic Journal*, 105, 429, pp. 333-344.

BERMAN, E., BOUND, J., GRILICHES, Z. (1994). – “Changes in the Demand for Skilled Labor in US Manufacturing Industries: Evidence from the Annual Survey of Manufactures”, *Quarterly Journal of Economics*, 109, pp. 367-98.

COCKBURN, I., GRILICHES, Z. (1988). – “Industry Effects and Appropriability Measures in the Stock Market’s Valuation of R&D and Patents”, *American Economic Review*, 78(2), pp. 419-23.

GEROSKI, P. (1991). – “Innovation and the Sectoral Sources of UK Productivity Growth”, *Economic Journal*, 98, pp. 375-390.

GEROSKI, P. (1995). – *The Science Policy Research Unit’s Innovation Database*, Oxford University Press, forthcoming.

GEROSKI, P., MACHIN, S., VAN REENEN, J. (1993). – “The Profitability of Innovating Firms”, *Rand Journal of Economics*, 24, 2, pp. 198-211.

GRILICHES, Z. (1984). – *R&D, Patents and Productivity*, Chicago University Press.

HAMERMESH, D. (1993). – *Labor Demand*, Princeton University Press.

HAMERMESH, D., PFANN, G. (1994). – “Adjustment Costs in Factor Demand”, *NBER mimeo*.

HILLIER, G. (1990). – “On the Normalisation of Structural Equations: Properties of Direction Estimators”, *Econometrica*, 56, pp. 1371-1395.

HOLTZ-EAKIN, D., NEWEY, W., ROSEN, H. (1988). – “Estimating Vector Autoregressions with Panel Data”, *Econometrica*, 56, pp. 1371-1395.

LEVIN, R., KLEVORICK, A., NELSON, R., WINTER, S. (1987). – “Appropriating the Returns from Industrial R&D”, *Brooking Papers on Economic Activity*, pp. 783-820.

MACHIN, S. (1995). – “Changes in the Relative Demand for Skills in the UK Labour Market”, in A. Booth and D. Snower, *Acquiring Skills*, Cambridge: Cambridge University Press.

MACHIN, S., MANNING, A., MEGHIR, C. (1993). – “Dynamic Models of Employment Based On Firm-Level Panel Data”, in J. C. van Ours, G. A. Pfann and G. Ridder, *Labor Demand and Equilibrium Wage Formation*, Elsevier Science Publishers.

PAKES, A. (1986). – “Patents as Options: Some Estimates of the Value of Holding European Patent Stocks”, *Econometrica*, 54, pp. 755-784.

ROBSON, M., TOWNSEND, J. (1984). – “Users Manual for the ESRC Archive File on Innovations in Britain since 1945”, *mimeo Science Policy Research Unit*, Univeristy of Sussex.

ROTA, P. (1994). – *Labour Demand and Adjustment Costs*, PhD Thesis, University College of London.

SOLOW, R. (1957). – “Technical Change and the Aggregate Production Function”, *Review of Economic sand Statistics*, pp. 312-320.

SHANKERMAN, M., PAKES, A. (1986). – “Estimates of the Value of Patent Rights in European Countries during the Post 1950 Period”, *Economic Journal*, 196, pp. 1052-76.

STERLACHINNI, A. (1989). – “R&D, Innovations and Total Factor Productivity growth in British manufacturing”, *Applied Economics*, 21, pp. 1549-1562.

THEIL, W. (1971). – *Principles of Econometrics*, New York: Wiley.

VAN REENEN, J. (1994). – "Employment, Innovation and Union Bargaining Models: New tests and evidence using UK Panel Data", *Centre for Economic Policy Research Discussion Paper No. 874*.