Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms

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This article uses British firm-level panel data on actual innovative activity drawn from different statistical sources to identify the effect of technical change on jobs. Previous work tends to find positive associations of proxies for technical change and employment, but such studies suffer from various statistical drawbacks. In this study, even when one controls for fixed effects, dynamics, and endogeneity, innovations have a positive and significant effect on employment, which persists over several years. There seems to be little direct role for spillover effects from industry innovations, or any role for industry wages or union power.

I. Introduction

> The opinion entertained by the laboring class that the employment of machinery is frequently detrimental to their interests is not founded upon prejudice and error, but is conformable to the correct principles of political economy. (RICARDO 1821)

The effects of technical change on employment have fascinated scholars and alarmed the general public down through the ages. For

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example, in the British Social Attitudes Survey in 1990 (Brook, Taylor, and Prior 1991), 63.9% of respondents believed that new microelectronic technologies would cause job loss compared to 8.8% who thought there would be gains. But the public has a rather schizophrenic attitude as innovation is also seen as a major driving force behind job creation.[1] That there should be intense disagreement on these matters is not surprising to economists. Although the required labor per unit of output is lower, technical progress that reduces the effective cost of labor will cause a firm to increase output. Which of these two effects dominates is the crucial factor in evaluating the effect of technology on employment. Innovations improving the range or quality of products offered by a firm will also tend to increase the firm's output. Nonneutral technical change (in the Hicksian sense) will also be associated with changes in the factor mix. The key question addressed in this article is a simple one: Is there a negative or positive association between innovation and employment at the firm level? The answer, which emerges through a variety of statistical tests, is clear. There is a strong positive association. This is true even after controls for fixed effects and dynamics have been added to a standard model of labor demand. The correlation is not simply driven by the fact that large firms innovate more but appears to be causal.

Despite the long-standing interest in technology and employment, there is a dearth of microeconometric studies on the effect of innovation on employment. Part of the reason for this is data driven. It is difficult to obtain firm-specific measures of technology on a consistent basis over time. Furthermore, when this information is available one must control for the fact that technology as well as employment are chosen by the firm. Dealing with the simultaneity problem requires some observable, exogenous but firm-specific technological shocks. The main contribution of this article is to use firm data on actual innovative activity drawn from different statistical sources to identify the effect of technical change on jobs. The analysis looks not only at what happens when a firm innovates but what happens when it does not, but its competitors do. The plan of action is as follows. Section II briefly summarizes recent microeconometric work on technical change and employment, Section III sketches some theoretical considerations, and Section IV contains the econometric

[1] In another part of the same British Social Attitudes Survey, respondents were asked how new technology had affected jobs at *their* workplace. About 13% thought it had increased the number of employees, 14% thought it had reduced them, and 48% said it had made no difference.

modeling strategy. Section V contains a detailed data description and Section VI holds the results. Section VII offers some conclusions.

II. Microeconometric Research on Technological Innovation and Employment

Most studies on the employment effects of technological innovation have been based on case studies of particular firms or technologies. They generally find that jobs are shed after the introduction of new techniques and appear to form the empirical basis of the layperson's fears.[2] Yet these studies tend to overlook the output expansion effect of innovations and ignore the counterfactual of what would have happened had the firm not innovated. To analyze these issues one must turn to statistical research.

Econometric work has focused on new technology-skill complementarities. This should be reflected in a higher demand for skilled workers relative to unskilled workers after technical change has occurred. A selection of recent work is given in table A1. There is general agreement that these complementarities exist, and Hamermesh (1993) goes as far as to claim, "We are fairly sure that technological change is . . . complementary with skill" (p. 135). More directly relevant to this article, however, is econometric work on the effects of innovation on total employment growth.

Many studies, following Salter (1966), have focused on the industry level of aggregation. Salter reported a positive association of total factor productivity growth with employment growth. In the United Kingdom, the relationship between the Solow residual and industry employment appears to have weakened since 1945 and practically disappeared in the 1970s (Wragg and Robertson 1978; Ball and Skeoch 1981). More ambitiously, Nickell and Kong (1989) estimated a three-equation (production, pricing, and demand) structural system across nine manufacturing industries between 1974 and 1985. Labor augmenting technical change was found to depress employment in only two of these industries (bricks and glass and textiles). In none of these studies is technical change explicitly observed; it is always taken as a trended residual. Thus, effects that are attributed to technology may really merely reflect omitted variables such as the quality of labor, monopoly power, or changes in effort.

One of the few studies at the company level using innovation counts is by Entorf and Pohlmeier (1991), who examined a large sample of

[2] For a collection of case studies see inter alia Rothwell and Zegveld (1979). An example of an engineering study is Fleck (1984), who predicted a loss of 1.4 jobs per robot introduced in an "average" plant.

German firms in 1984. Their simultaneous model of exports, innovation, and employment suggests that product (but not process) innovations significantly increase employment. Unfortunately, the use of only a single cross section prevents any analysis of dynamics or controls for individual fixed effects.

At the establishment level both Machin and Wadhwani (1991) and Blanchflower, Millward, and Oswald (1991) use the 1984 British Workplace Industrial Relations Survey (WIRS) to examine employment determination. In both studies the adoption of new microelectronic technologies has a negative raw correlation with employment growth. Controlling for workplace characteristics reveals that the conditional correlation is actually positive. Similar positive findings are also found in the most recent wave of the British WIRS in 1990 and its Australian counterpart in 1989 (Blanchflower and Burgess 1995). Doms, Dunne, and Roberts (1994) use U.S. data to examine the employment growth of plants using a greater number of advanced manufacturing technologies. They also find positive effects on both employment growth and plant survival. Unlike the U.K. studies, they were also able to include proxies for the capital stock. In summary then, and against popular conceptions, the small applied literature does suggest that technical change, defined in a variety of ways, has a positive effect on jobs. Firms that fail to keep up with the adoption of new technologies appear to suffer slower growth. There remain, however, some serious problems affecting these studies. None really deals with correlated fixed effects due to the absence of longitudinal data on new technologies. Furthermore, it is very difficult to control for the endogeneity of technology and employment choice. The empirical sections attempt to deal with these twin problems by utilizing original types of data.

III. Employment and Technical Change: Theory

There are a large number of ways in which economists have theorized about how technology affects employment. In this section a few key distinctions are made and the simple microeconomics of labor demand summarized. The aim is to enable a better understanding of the different interpretations that can be made of the results in the empirical sections.

One key distinction is between product innovations (which change the demand function) and process innovations (which change the production function). Analysis has tended to focus on the latter rather than the former, perhaps because of the view that product innovations will always be associated with higher employment. A new product will generate new demand and (in the absence of any process element) this should raise labor demand. Of course, if a firm produces multiple products, new goods may drive out old goods so this will reduce the overall expansion in labor demand.[3]

A second important distinction is whether a process innovation is immediately (and costlessly) diffused throughout an industry or whether adoption is slow. Clearly, the gradual imitation of best practice is more realistic and is the basis of the Schumpeterian view of economic change. Nevertheless, the standard approach is to assume that all firms in an industry use the same technology. Turning first to this approach, the effect of different types of disembodied process innovations on employment will depend on the relative importance of several factors.[4] Crucially, labor-saving technical progress reduces the required labor input per unit output, but by reducing costs there is an offsetting output expansion effect.

The following model illustrates some of the trade-offs. Consider a perfectly competitive industry operating under a constant returns constant elasticity of substitution production function of the form

$$Q = T[(AN)^{(\sigma - 1)/\sigma} + (BK)^{(\sigma - 1)/\sigma}]^{\sigma/(\sigma - 1)}, \tag{1}$$

where Q = output, N = employment, and K = capital; T represents a Hicks-neutral technology parameter, movements in T leave the capital-labor ratio unchanged; A represents labor augmenting Harrod-neutral technology (which leaves the output-capital ratio unchanged); and B represents Solow-neutral technical change (output-capital ratio fixed). Since real wages (W/P) are equated with the marginal product of labor, the first-order condition for labor can be written as

$$\log N = \log Q - \sigma \log(W/P) + (\sigma - 1)\log A. \tag{2}$$

[3] Katsoulacos (1986) gives a full treatment of the short-run and long-run effects of product innovation. Examining models of both horizontal and vertical product differentiation, he concludes that his theoretical results give support to the "often quoted empirical observation . . . that product innovation is more likely to have a favourable employment effect than process innovation" (p. 12).

[4] *Embodied* technological progress requires the adoption of new methods and inputs to raise productivity (e.g., Eli Whitney's cotton gin). Unfortunately embodied technical change is very difficult to analyze in a tractable way.

The elasticity of labor with respect to a change in labor-saving technology, A, is given by

$$\frac{\partial \log N}{\partial \log A} = \left(\frac{\partial \log Q}{\partial \log P}\right)\left(\frac{\partial \log MC}{\partial \log A}\right) + (\sigma - 1),$$

where we use the fact that in the competitive industry price is set equal to marginal cost (MC). This can be also expressed as

$$\eta_{NA} = \eta_p \theta + (\sigma - 1), \tag{3}$$

where η_{NA} is the employment-technology elasticity, the price elasticity of demand is η_p, and the elasticity of marginal cost with respect to technical change is θ. For a fixed level of output, the effect of technical change on employment will depend on the degree of substitutability between capital and labor (which is now relatively cheaper). When this elasticity is high ($\sigma > 1$), labor demand will rise. When output and capital are allowed to vary, positive employment effects are still possible even for a low elasticity of substitution ($\sigma < 1$) as lower industry prices will increase consumer demand. Positive employment effects are more likely, the greater the sensitivity of demand to price (η_p) and the "larger" the size of the innovation (θ).[5]

This is from the perspective of an industry, but what of the perspective of the firm? If diffusion was immediate the employment effects should be the same regardless of who innovates first in an industry. Thus, innovations may differ across industries but are shared by all firms in the same industry. When an innovation diffuses slowly around the industry, the first adopting firms will enjoy increases in their market share over and above any output expansion effects that eventually occur industrywide. An innovation that has a negative effect on industry employment will be temporarily offset by the fact that the first firm to innovate will enjoy a (temporary) increase in its market share.

Theoretically, the effects of innovation are ambiguous and it is an empirical issue which factors will dominate. Nevertheless, there are

[5] For more detailed treatments, see Neary (1981), Sinclair (1981), and Dowrick and Spencer (1994).

other reasons why a spurious positive relationship could be generated that have not yet been touched upon. The first is due to other unmeasured factors in the production function. Higher quality organizations may find it less costly to innovate and also have higher output due to superior efficiency. If this is not properly measured then the effects of innovation on employment will appear artificially high. This is essentially a problem of correlated firm-specific effects. Second, there is an issue of demand expectations. Employment will grow if the firm expects demand to increase, but it may also commercialize new innovations to capture a greater part of this growing market (see Shleifer [1986] for a formalization of this view). This theoretical possibility is unlikely given the nature of the innovation data. A firm may want to innovate in response to a demand shock, but it is assumed that innovation is a costly business involving R&D expenditures with long gestation periods that cannot be adjusted easily from year to year. Nevertheless, the econometric modeling strategy attempts to deal with both of these problems.

IV. Econometric Modeling Strategy

Consider the simple labor demand relationship in (2). We can substitute for output using the equivalent first-order condition for capital (R is the cost of capital):

$$\log N = (\sigma - 1)\log(A/B) - \sigma \log W + \log K + \sigma \log R. \tag{4}$$

Replacing the unobserved technology variables with proxies for innovation (INNOV), the basic stochastic form of this model becomes

$$n_{it} = \alpha_1 \text{INNOV}_{it} + \beta_3 w_{it} + \beta_4 k_{it} + \tau_t + u_{it}. \tag{5}$$

Lower case letters denote natural logarithms, τ_t is a full set of time dummies, and u_{it} is a white noise error term. The most straightforward interpretation of (5) is an industry labor demand curve where the cost of capital is assumed to be constant across firms and proxied by time dummies, τ_t. Under this interpretation $\beta_3 = \sigma$, the elasticity of substitution. In the longer run, capital can be adjusted and so for estimation purposes one could substitute out capital for input and output prices. This effectively means dropping capital from the estimating equation ($\beta_4 = 0$) and considering (5) as the uncompensated labor demand equation. The empirical sections experiment with this alternative specification.

There are several remaining problems with this specification. First, the model is entirely static yet it is likely that costs of adjustments will induce dynamics into (5). A formulation of two lags in employment is allowed for, as suggested by previous U.K. studies.[6] Furthermore, innovation itself is an inherently dynamic process and is likely to have long and persistent effects. Therefore lags up to 6 years (and in some cases 10 years) are included.

Second, the problem of unobserved correlated effects could bias the estimate of the innovation terms as detailed at the end of the last section. Consequently the main results show the first-differenced estimates that should sweep out the effect of managerial quality and other unobserved factors that are reasonably stable over time. First differencing is attractive compared to including a full set of firm dummies (the "within groups" estimator) as the panel is short in the time dimension. The bias in short panels from the use of within groups can be severe since the control variables are not strictly exogenous.[7]

Finally, one must deal with the potential endogeneity of many of the variables. First differencing immediately leads to the problem that the lagged dependent variable, Δn_{it-1}, will be correlated with the error term, Δu_{it} by construction. Ordinary least squares (OLS) estimates of the parameter on the lagged dependent variable will be biased downward and this endogeneity bias will in general affect all the other coefficient estimates. To deal with this it is necessary to use instrumental variables. In the absence of serial correlation in the u_{it} process, lags of employment at or before $t - 2$ are valid instruments. This is because the moment restriction $E(n_{it-2}\Delta u_{it}) = 0$ is valid where $E(\cdot)$ is the expectations operator. Also, with employment adjustment costs, lags of employment are correlated with current employment since $E(\Delta n_{it-1} n_{it-s}) \neq 0, s \geq 2$. As the panel progresses more moment restrictions become available that can be used to create an efficient

[6] The first lag can also be rationalized as resulting from quadratic adjustment costs in net employment changes. The second lag could be due to aggregation over skilled and unskilled workers (Nickell 1984).

[7] Strict exogeneity implies that shocks to current employment (u_{it}) have no effect on the future values of the right-hand-side variables. This is an assumption that is clearly ruled out in dynamic models that include lagged values of the dependent variable. Nickell (1981) shows that the size of this bias declines as the time dimension of the panel increases.

general method of moments (GMM) estimator.[8] This technique has recently been proposed by Arrellano and Bond (1991) and Holtz-Eakin, Newey, and Rosen (1988). To check on the validity of the serial correlation assumption and the exogeneity of the instruments, full diagnostics are given in the Results Section.

Unfortunately, problems of endogeneity are not confined to the lagged dependent variable. Both capital and wages may also be choice variables for the firm. Furthermore, the wage variable is constructed from payroll data so random measurement error in employment could bias the relationship between employment and wages. Consequently in some specifications both wages and capital are also instrumented. Recall that firm innovations are not instrumented in the main results because they are taken to be predetermined to the employment decision. Nevertheless, as a check on this assumption two strategies are used. First, the time dummies (τ_t) included in all specifications should control for general macroeconomic demand shocks. Second, an experiment is conducted using the past patenting activity of the firm as an instrument for current innovations. The idea here is that the firm builds up a stock of blueprint technologies (patents) that can be actualized in the form of an innovation when economic conditions are favorable. On this view of the technological change, past patenting activity should not be a determinant of current employment but will have an effect on current innovation probabilities. This should deal with the second problem discussed at the end of Section III.

Taking these factors into consideration, the main model that is estimated has the general form

$$\begin{aligned} n_{it} = f_i &+ \sum_{j=0}^{6} \alpha_{1j}\mathrm{INNOV}_{it-j} + \sum_{j=0}^{1} \alpha_{2j}\mathrm{IUI}_{it-j} + \sum_{j=0}^{1} \alpha_{3j}\mathrm{IPI}_{it-j} \\ &+ \beta_1 n_{it-1} + \beta_2 n_{it-2} + \beta_3 w_{it} + \beta_4 k_{it} + \tau_t + u_{it}, \end{aligned} \tag{6}$$

where IUI and IPI are industry innovations used and produced. These are designed to reflect the different technological opportunities and potential spillovers in the firm's principal industry and are further discussed below.

[8] For example, since the first year of estimation is 1979, instruments dated in 1977 or 1976 are valid. In 1980 instruments dated in 1978, 1977, and 1976 are valid and so forth. See Arellano and Bond (1991) for a full description of this technique.

V. Data

The data set used in this study is a rich and unique combination of several sources (see the data appendix for a full description). The primary database is a panel of manufacturing firms listed on the London Stock Exchange for at least 5 continuous years between 1976 and 1982. There are 598 firms in all employing over 3 million workers in 1980 (48% of all U.K. manufacturing employment). Innovation count data drawn from the Science Policy Research Unit's (SPRU) innovation database was matched to the accounts data. The SPRU data contain 4,378 innovations commercialized in Britain since World War II. The data collection was done in three waves (1970, 1980, and 1983). A large number of experts from science, industry, and academia were asked to identify the "successful commercial introduction of new or improved products and processes" (Robson and Townsend 1984, p. 2) introduced in Britain between 1945 and 1983. The experts were chosen to reflect their different specialties in different industrial branches. After collecting details of the innovations, the SPRU team contacted the firms who had first commercialized them for more information on the company's characteristics and the timing of the innovation.

The SPRU data set has been used extensively by economic researchers but mainly at the industry level. For example, econometric work by Geroski (1991) and Sterlachinni (1989) established a statistically significant link between the numbers of innovations used in an industry and productivity growth. Machin (1995) found that the lagged number of SPRU innovations used in 16 manufacturing industries is a significant predictor of the growth in the employment share of nonproduction workers during 1980–85.

It might be thought that the SPRU definition of "successful" innovation guarantees positive employment effects, but this is not the case. First, commercial success was considered in terms of profitability and productivity rather than employment. It could easily be coupled with a reduction of the workforce. Second, the notion of commercial success is not necessarily closely tied to the company that first introduced the innovation. The British company EMI, which introduced the technologically significant and commercially successful CAT body scanner, actually suffered a loss from the project (about $40 million during 1977–79). It was the technological followers, General Electric and Technicore, that realized the greatest profit gain.

Matching the innovations to company accounts information allowed the construction of a count of the number of innovations a firm commercialized 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, not just the sample that we happen to estimate on. In all about a third of the innovations in the SPRU manufacturing population are contained in our data set. The losses are mainly due to the absence of smaller nonlisted companies from our data, which 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 all the way back to 1945, a long lag structure can be allowed for, even though adequate accounting data are available only from 1976. What are the advantages of using the innovations data and are they 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 that do, most innovate 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, e.g., Pakes 1986). To draw this contrast out, U.S. patents taken out by U.K. firms were also matched to the data set. The two variables are reasonably correlated and share a similar distribution across firms.[9] There are a total of 220 innovations by the firms during 1976–82 compared to 4,669 patents. It is therefore unsurprising that profitability regressions on these data suggest that the return to an average SPRU innovation is far higher than the return to a typical patent.[10]

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. The R&D expenditures are problematic because many firms report no formal R&D and yet manage to innovate.[11] This is because many smaller firms are involved in informal search for new technologies without having R&D labs.

The employment variable used is total U.K. employment (firms did not have to disclose this after 1982). The wage is derived by dividing total U.K. remuneration by U.K. employment and deflating by an aggre-

[9] 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).

[10] Geroski, Machin, and Van Reenen (1993) calculated that the average long-run value of a SPRU innovation was about $3 million at 1985 prices. Shankerman and Pakes (1986), using option values on British patents, calculate a median value of $1,861.

[11] This is a particular problem in the United Kingdom over this period as accounting regulations governing R&D disclosure were very weak until 1989.

Table 1
Descriptive Statistics

	All		Innovators*		Noninnovators	
Mnemonic	Mean	SD	Mean	SD	Mean	SD
INNOV	.043	.294	.173	.569	0	0
INNOV (product)	.034	.249	.135	.484	0	0
Patents	1.134	7.880	4.233	15.330	.100	.509
Employment (1,000s)	4.827	12.189	11.376	18.186	2.642	8.300
Real wage (£1,000s)	6.748	1.530	7.340	1.255	6.552	1.564
Capital (£100 million)	.489	2.114	1.373	3.982	.184	.568
Industry innovations:						
Produced	8.001	12.781	10.488	14.000	7.171	12.240
Used	3.657	4.706	4.578	5.024	3.350	4.555
Industry R&D/sales	.010	.015	.012	.018	.009	.014
Industry wage	7.302	1.321	7.700	1.014	7.170	1.384
Union density	.705	.136	.728	.123	.698	.139
Number of observations	2,039		510		1,529	
Number of firms	598		149		449	

NOTE.—All variables in 1985 prices; number of observations refers to estimating sample from 1979–82.
* An innovating firm is one that innovated at least once within or presample.

gate price index.[12] Capital 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, that will alter the implied value of different capital vintages. Instrumenting with lagged values will mitigate some of the measurement error problem, but one should not pretend that the capital measure derived from company accounts is anything but a crude proxy for the true variable of interest.

Means, standard deviations, and sources of data are contained in table 1. Just over 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 and capital stocks.[13] Unsurprisingly they tend to be located in industries with larger numbers of innovations and R&D intensities. Despite the concentration of innovative activity in some sectors, most of the variance in innovative activity is between the firms *within* the three-digit industrial groupings.

[12] Obviously one would like a better measure of the contract wage taking hours and skill composition into account, but this is simply not available at the company level.

[13] Van Reenen (1996) examines the effect of innovations on wages in the context of a rent-sharing model of wage bargaining.

Table 2
Employment and Innovation: Descriptive Regressions

Log Employment	Levels (1)	Levels (2)	Changes (3)	Changes (4)
$INNOV_t$	.3352	.3613	.0218	.0220
	(.0874)	(.0888)	(.0103)	(.0105)
$INNOV_{t-1}$	.2979	.2832	.0243	.0222
	(.0881)	(.0897)	(.0116)	(.0120)
$INNOV_{t-2}$	.2907	.2847	.0232	.0203
	(.0865)	(.0872)	(.0139)	(.0142)
$INNOV_{t-3}$	.4028	.4333	.0275	.0262
	(.0886)	(.0904)	(.0153)	(.0155)
$INNOV_{t-4}$	.3393	.3533	.0208	.0200
	(.0904)	(.0925)	(.0159)	(.0161)
$INNOV_{t-5}$	.2629	.2267	.0068	.0061
	(.0951)	(.0988)	(.0151)	(.0155)
$INNOV_{t-6}$	.2518	.3178	.0110	.0127
	(.1006)	(.1059)	(.0113)	(.0117)
$PATENT_t$	...	.0468	...	.0013
		(.0129)		(.0013)
$PATENT_{t-1}$	...	.0043	...	.0000
		(.0133)		(.0013)
$PATENT_{t-2}$	...	−.0373	...	.0002
		(.0130)		(.0012)
$PATENT_{t-3}$	...	−.0064	...	.0005
		(.0124)		(.0012)
$PATENT_{t-4}$	...	.0200	...	.0013
		(.0144)		(.0015)
$PATENT_{t-5}$	...	−.0145	...	.0013
		(.0113)		(.0015)
$PATENT_{t-6}$	...	−.0062	...	.0007
		(.0101)		(.0014)
Constant	.2227	.2161	−.0260	−.0258
	(.0241)	(.0241)	(.0028)	(.0028)

NOTE.—Sample period, 1977–82; estimation by pooled ordinary least squares; 598 firms and 3,235 observations. Standard errors in parentheses.

VI. Results

As the first step in the econometric analysis, table 2 contains OLS regressions of employment on innovations and patents. In columns 1 and 2 these are in levels and in 3 and 4 these are in first differences. In column 1 current and lagged innovations are significantly and positively correlated with firm employment. The next column adds patents. The innovation terms all remain singularly and jointly significant whereas the patent coefficients are all smaller and less well determined. Current patents are significantly positive, but longer lags are either negative or insignificant. Since employment and technology are likely to be permanently higher in some firms due to fixed effects, columns 3 and 4 present the first-differenced results. Although weaker, the innovation effects remain significant. By contrast, patents were uniformly positive but quite insignificant. This suggests that, conditional on innovation, changes in firm patenting activity have no significant association with employment growth. Table 2 leaves out many important controls from the employment equation. Consequently, table 3 builds up to a more complex and theoretically satisfactory specification. Since two longer lags are introduced on employment, the sample period is shortened to 1979–82. In column 1 capital and lagged employment are added to the equation. These are all well determined and enter with their expected signs. As with many U.K. studies, the second lag of employment enters with a significant negative effect (e.g., Nickell and Wadhwani 1991). The sum of the lag coefficients is less than unity implying the model is dynamically stable. These size measures reduce the point estimates on the firm-level innovation measures. In column 2 time dummies and the wage are also included; the latter has a well-determined point estimate of around −0.3. In the next column industry innovations used and produced are also included. There is a little evidence of positive employment spillovers from the lagged number of industry innovations produced, but their point estimates are far smaller than the own-firm innovation effects, suggesting that innovations are not immediately spread throughout the industry.[14]

Dynamic first-differenced models suffer from bias due to the correlation of the lagged dependent variable with the error term. Lagged employment is therefore instrumented in column 4. As expected there appears to be rather severe downward bias on the lagged employment term in the OLS results. Diagnostics regarding the second-order serial correlation test and the Sargan test of instrument exogeneity fail to reject the null of instrument validity. Since wages and capital may also suffer endogeneity bias, they are also instrumented in column 5. The instrumental variables (IV) estimates do not fundamentally alter the pattern of results, but they do suggest some downward bias in the pure OLS estimates for the coefficients on capital and innovations. On the basis of column 5 the short-run compensated labor demand elasticity is 0.15 (= 0.491 *0.3),[15] although the standard error around this estimate is large. The industry innovations effects are all driven to insignificance in the IV results.

[14] Allowing longer or shorter lag structures on the industry innovation terms (up to $t - 6$) failed to shake this result.

[15] This calculation assumes that labor's share of value added is 70%.

In column 6 the capital stock variable is dropped. As expected the coefficient on the wage terms rises, reflecting the fact that substitution possibilities are much greater if capital is allowed to vary. The innovation terms remain strong and significant, however, and the implied "long-run" effects are somewhat larger (an effect of 0.35 in col. 6 compared to 0.28 in col. 5).[16]

To investigate the robustness of these results, some further experiments are contained in table 4. The first column examines the potential endogeneity of innovations, the second adds longer lags, the third splits up product from process innovations, and the final column looks at misspecifications of the employment rule due to union bargaining.

Consider first the problem of the endogeneity of innovations. Patenting may be a good proxy for a firm's stock of inventions and is one of the few series whose past values are correlated with *changes* in current innovations.[17] The results in column 1 instrument current and lagged innovations with patents lagged at least three periods. Although the standard errors have risen, the coefficients are basically unchanged and, if anything, larger.

The long history of the innovations data is exploited in column 2 which adds lags of firm innovations up to $t - 10$. An interesting pattern emerges of a tendency toward more negative coefficients as time goes on. Taking the dynamics into account suggests that the effect of "an innovation" peaks after 6 years. Although the longer lags are imprecisely estimated, it is tempting to attribute this to the process of imitation and entry that sets in after an initial breakthrough. Eventually this reduces firm employment growth as the new technology becomes old technology. Care is needed in interpreting this pattern, however, as there is no natural unit of normalization for an innovation.

Product innovations are more likely to increase labor demand than process innovations. Distinguishing between these types of technical change is difficult, conceptually as well as empirically, as many innovations naturally have elements of both. The data collectors (Pavitt, Robson, and Townsend 1987) suggest splitting the innovations into those which were first used in a different two-digit industry to the main industry of the innovating firm. This is, of course, problematic

[16] These are calculated by solving for the long-run steady state. Using eq. (6) this means that the long-run effect is $(\Sigma_{j=0}^{6} \alpha_{1j})/(1 - \beta_1 - \beta_2)$. For col. 5 this means that the effect on log employment of "an" innovation is $0.172/(1 - 1.05 + 0.67)$.

[17] A regression of the change in innovations against patents $(t - 2)$ and $(t - 3)$ gives an $F(2, 3235) = 8.4$.

Table 3
Employment Growth and Innovation

Log Employment	OLS (1)	OLS (2)	OLS (3)	GMM (4)	GMM (5)	GMM (6)
Firm variables:						
$INNOV_t$	.0170	.0159	.0160	.0215	.0345	.0332
	(.0091)	(.0092)	(.0092)	(.0097)	(.0111)	(.0119)
$INNOV_{t-1}$	.0182	.0122	.0121	.0161	.0293	.0183
	(.0112)	(.0122)	(.0123)	(.0098)	(.0140)	(.0130)
$INNOV_{t-2}$	.0153	.0098	.0086	.0196	.0363	.0340
	(.0121)	(.0122)	(.0121)	(.0162)	(.0171)	(.0205)
$INNOV_{t-3}$	.0171	.0116	.0113	.0226	.0356	.0353
	(.0138)	(.0146)	(.0145)	(.0135)	(.0149)	(.0185)
$INNOV_{t-4}$	.0145	.0074	.0074	.0125	.0166	.0119
	(.0117)	(.0116)	(.0115)	(.0127)	(.0193)	(.0176)
$INNOV_{t-5}$	.0151	.0110	.0100	.0133	.0222	.0111
	(.0103)	(.0109)	(.0109)	(.0108)	(.0153)	(.0172)
$INNOV_{t-6}$	.0016	−.0022	−.0028	−.0069	−.0026	−.0112
	(.0104)	(.0105)	(.0102)	(.0145)	(.0193)	(.0233)
$EMPLOYMENT_{t-1}$	.1947	.1950	.1933	.8617	1.0530	1.3727
	(.0273)	(.0295)	(.0294)	(.2613)	(.2112)	(.2113)
$EMPLOYMENT_{t-2}$	−.0688	−.0723	−.0710	−.0888	−.6726	−.7508
	(.0308)	(.0286)	(.0291)	(.2727)	(.1724)	(.1988)
$CAPITAL_t$	.4378	.4133	.4119	.3445	.6038	...
	(.0336)	(.0339)	(.0340)	(.0401)	(.2632)	
$WAGE_t$	...	−.3150	−.3141	−.4274	−.4912	−.9501
		(.0862)	(.0866)	(.1118)	(.3548)	(.2801)

Industry variables:*						
INNOVs PRODUCED$_t$	...	...	.0453	.0013	−.0183	−.1033
			(.0553)	(.0756)	(.0915)	(.1005)
INNOVs PRODUCED$_{t-1}$	...	...	.1544	.1109	.0811	.1175
			(.0602)	(.0786)	(.0899)	(.1035)
INNOVs USED$_t$	...	...	.0066	.0310	−.1518	.0092
			(.1258)	(.1780)	(.2034)	(.2196)
INNOVs USED$_{t-1}$	...	...	−.0902	−.1512	−.2355	−.2502
			(.1112)	(.1673)	(.1795)	(.2205)
Time dummies	No	Yes	Yes	Yes	Yes	Yes
Instrumented variables	No	No	No	n_{t-1}	n_{t-1}, w_t, k_t	n_{t-1}, w_t
Sargan test (df):	...	...	...	8.324(8)	20.133(17)	18.92(18)
(p-value)				.403	.267	.397
Serial correlation:	−1.165	−.980	−1.034	−.770	1.356	.639
(p-value)	.244	.327	.301	.442	.175	.523
Number of firms	598	598	598	598	598	598
Number of observations	2,039	2,039	2,039	2,039	2,039	2,039

NOTE.—OLS = ordinary least squares, GMM = general method of moments. All variables in first differences; estimation period 1979–82 (instruments from 1976); all SEs are in parentheses and adjusted for heteroscedasticity and autocorrelation of unknown form; cols. 1–3 estimated by OLS; cols. 4–6 by GMM; Sargan is an overidentification test of the exogeneity of instruments. It is distributed χ^2 ($\rho - k$) under the null, ρ = number of instruments, k = number of variables in regression. Second-order serial correlation test is basically a LaGrange multiplier (LM) test distributed $N(0,1)$ under the null of no autocorrelation—see Arellano and Bond (1991).

* All coefficients and SEs are scaled up by 100 on industry innovations.

Table 4
Employment and Innovation: Robustness Checks

Log Employment	(1) Patents as IVs	(2) Long Lags	(3) Products	(3) Processes	(4) Alternative Wage
Firm variables:					
$INNOV_t$	.0346	.0327	.0388	.0249	.0352
	(.0187)	(.0112)	(.0138)	(.0199)	(.0111)
$INNOV_{t-1}$	.0365	.0278	.0438	.0001	.0302
	(.0280)	(.0135)	(.0178)	(.0262)	(.0138)
$INNOV_{t-2}$	.0404	.0307	.0478	.0086	.0364
	(.0211)	(.0161)	(.0241)	(.0261)	(.0167)
$INNOV_{t-3}$	.0410	.0293	.0594	−.0007	.0354
	(.0235)	(.0160)	(.0180)	(.0252)	(.0150)
$INNOV_{t-4}$	.0199	.0052	.0252	.0202	.0168
	(.0263)	(.0211)	(.0242)	(.0331)	(.0197)
$INNOV_{t-5}$	.0244	.0086	.0420	−.0120	.0237
	(.0173)	(.0181)	(.0179)	(.0345)	(.0151)
$INNOV_{t-6}$	−.0007	−.0181	.0006	.0186	.0013
	(.0198)	(.0220)	(.0199)	(.0306)	(.0190)
$INNOV_{t-7}$	...	−.0248	...		...
		(.0191)			
$INNOV_{t-8}$	...	−.0104	...		...
		(.0240)			
$INNOV_{t-9}$	...	−.0003	...		...
		(.0177)			
$INNOV_{t-10}$	...	−.0105	...		...
		(.0114)			
$EMPLOYMENT_{t-1}$	1.0065	1.0430	1.0023		1.0114
	(.2026)	(.2151)	(.2184)		(.2136)
$EMPLOYMENT_{t-2}$	−.6396	−.6682	−.6478		−.6620
	(.1645)	(.1731)	(.1716)		(.1722)
$WAGES_t$	−.4228	−.4615	−.4652		−.4764
	(.3142)	(.3577)	(.3670)		(.3665)
$CAPITAL_t$	.6199	.6123	.6599		.6568
	(.2365)	(.2692)	(.2641)		(.2501)

Industry variables:				
INNOVs PRODUCED$_t$*	−.0104	−.0155	.0014	.0016
	(.0872)	(.0914)	(.0898)	(.0930)
INNOVs PRODUCED$_{t-1}$*	.0815	.0802	.0808	.0974
	(.0870)	(.0889)	(.0892)	(.0964)
INNOVs USED$_t$*	−.1457	−.1545	−.1673	−.1686
	(.1957)	(.2027)	(.1997)	(.2041)
INNOVs USED$_{t-1}$*	−.2253	−.2435	−.2022	−.2151
	(.1757)	(.1788)	(.1715)	(.1777)
IND WAGE$_t$	...	...	...	.1132
				(.1310)
IND WAGE$_{t-1}$	...	...	...	.1816
				(.1448)
UNION DENSITY$_t$	...	...	...	−.0199
				(.0699)
UNION DENSITY$_{t-1}$	...	...	...	.1543
				(.1224)
Sargan test (df):	28.345(25)	19.671(17)	21.373(17)	21.946(17)
(p-value)	.292	.291	.210	.187
Serial correlation:	1.342	1.384	1.294	1.348
(p-value)	.180	.166	.196	.178
Number of firms	598	598	598	598
Number of observations	2,039	2,039	2,039	2,039
Time dummies	Yes	Yes	Yes	Yes

NOTE.—All variables in first differences; estimation period 1979–82 (instruments from 1976); all standard errors are in parentheses and adjusted for arbitrary heteroscedasticity and autocorrelation of unknown form; all equations estimated by general method of moments: lagged employment, wages, and capital are all treated as endogenous—see table 3, col. 5; col. 1 instruments innovations with lagged patents; col. 3 splits innovations into product and process innovations.

* Coefficients and standard errors on the industry innovations terms multiplied by 100.

as many firms may do process innovations outside their main two-digit industries and product innovations within a two-digit industry. Nevertheless, allowing separate employment effects for each type in column 3 leads to quite striking results. The product innovation terms are larger and highly significant (joint test gave a $\chi^2(7) = 17.5$), whereas the process innovations have insignificant and small (often negative) effects.[18] The result is consistent with the theoretical prior that product innovations should lead to greater job creation. It may be, however, that the "process innovations" are merely picking up more incremental technical changes that are unlikely to have large effects on employment. Finally, recent extensions of union bargaining theory suggest that the model in its current form may be misspecified. This may be particularly a problem in our sample where union density is over 70%. When unions bargain over employment, additional terms reflecting the alternative wage and union density should have an independent influence on employment, even after conditioning on the own wage (Nickell and Wadhwani 1991). Current and lagged values of the industry wage (to proxy the alternative wage) and union density are included in the final column. It is clear that they are all individually and jointly insignificant ($\chi^2(4) = 4.895$). This result is not due to a fallacious mixing together of union and nonunion enterprises. Implementing the general model on a sample of 154 firms *where unions were recognized for the purpose of wage bargaining* rendered relatively similar results ($\chi^2(4) = 1.36$). This remained the case even under a wide variety of experiments with different definitions of the alternative wage.[19]

A number of other (unreported) experiments were performed on the data. First, it may be thought that innovation in itself represents a change of technology so the innovation terms should enter in levels in the first differenced specifications. Replacing all the innovation terms by levels led to rather poorly determined results, although the effect of an innovation remained positive and significant.[20] Second, expected demand should enter into the employment decision and we have assumed that this was reflected

[18] Note, however, that there are fewer process than product innovations and the imprecision reflects this to some extent.

[19] Other definitions included a weighted average of unemployment benefit levels and industry wages (where the weight reflected aggregate unemployment), industry unemployment, aggregate wages, aggregate unemployment, and various combinations of these.

[20] The estimates were 0.027(0.012), −0.006(0.013), 0.008(0.019), 0.000(0.019), −0.020(0.020), 0.005(0.017), and −0.028(0.016) on current innovation and the six lags.

in the time dummies. As an alternative, current and lagged industry sales growth was also included. The terms were never significant at conventional levels ($\chi^2(2) = 0.6$). Third, the dynamics were freed up to test whether longer lags in the variables may be preferable to just their current values. This never seemed to be the case.[21] Fourth, 14 broad industry dummies were included to test for industry-specific time trends that may be correlated with innovative behavior. They were jointly insignificant ($\chi^2(13) = 16.43$) and the results were not substantially changed.

VII. Conclusions

This article has used novel data on headcounts of innovation in a panel of 598 firms to examine an age-old question. The main finding is that technological innovation was associated with higher firm-level employment in our data set. This result seemed robust to a wide range of specifications and controls. Although the data show that big firms innovate most, even after using long lags on innovation and controlling for firm-fixed effects there is evidence of a correlation between employment and innovation. This suggests that we really are capturing causality from technical change to jobs. Part of the reason appears to be the fact that many of the innovations are in products rather than processes and these will be expected to have a stronger effect on employment.

Another interesting finding was the absence of spillovers or employment externalities from other firms in the industry. This is consistent with other analyses of these data examining profitability (Geroski, Machin, and Van Reenen 1993). One possibility for this result is that the positive industrywide effects on employment due to diffusion are canceled out by a rivalry effect as firms compete for market share.

To what extent are these results generalizable? It is likely that we may actually be underestimating the effects of innovation as no controls have been made for the fact that innovators are more likely to survive than noninnovators. Nevertheless, a useful extension of this work would be to consider the differential effect of technologies through their life cycle taking into account not only the first commercialization of an innovation but also its subsequent diffusion throughout the industry. The development of longitudinal databases of technologies and firms is a major task for those seriously concerned with the dynamic effect of innovation on jobs.

[21] For example, w_{t-1} and w_{t-2} took coefficients (SEs) of $-0.361(0.363)$ and $-0.131(0.214)$, respectively.

Data Appendix

The database combines several company data sets 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 during 1968–82. These are basically populations of all firms listed on the London Stock Exchange. Firms that had fewer than five continuous time series observations, whose principal operating industry (defined by sales) was outside manufacturing, or that were involved in large scale merger activity were removed from the sample.

ii) The SPRU innovations database. This consists of over 4,300 major innovations defined as "the successful commercial introduction of new or improved products, processes and materials introduced in Britain" during 1945–83. 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 midyear (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 trail-off toward 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 are less reliable than after this date. The aggregate innovations data display discernible peaks and troughs at roughly 5-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.

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

The data have been used extensively by U.K. researchers and a full bibliography is contained in Geroski (1995). The data themselves are lodged at the Economic and Social Research Council (ESRC) Data Archive at the University of Essex and are described in great length in Robson and Townsend (1984).

iii) Patents granted to U.K. firms by the U.S. Patents Office between 1969 and 1988. The decision to use U.S. patents rather than U.K. 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 598 firms between 1976 and 1982. The balance of the panel was as follows: 25 firms with 5 years of data, 303 firms with 6 years of data, and 270 firms with 7 years of data. Details of the means, standard deviations, and sources of all variables are in tables 1 and A2.

The definitions include:

Wages. Total U.K. remuneration divided by total U.K. employment. Until July 1982, companies were required to disclose the number of U.K. employees and remuneration. As of this date, the requirement was for group totals only (which includes overseas employment). The variable is exclusive of employer's payroll tax.

Employment. Total number of U.K. employees.

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

Appendix A

Microstudies of Employment and Technology

Table A1
Recent Microeconometric Studies of the Effects of Technological Change on Employment

Authors	Methodology	Level of Aggregation
A. Complementary of technology and skill:		
Bartel and Lichtenberg (1987)	Estimation of restricted variable cost function for labor	61 manufacturing industries in 1960, 1970, 1980
Berman, Bound, and Griliches (1994)	Decomposition of changes in employment share of nonproduction workers, 1979–89	Four-digit SIC, manufacturing
Berndt, Morrison, and Rosenblum (1991)	Regressions of labor intensity measures on "high-tech office equipment" capital intensity	Two-digit SIC industry
Lynch and Osterman (1989)	Labor demand curves for 10 occupational classes of workers	One Firm (Bell telephone company), 1980–85; year-state-occupation cell
Machin (1996)	Changes in employment shares of skilled workers regressed on technical change in two samples (industry and establishment)	16 U.K. manufacturing industries, 1982–89; panel of 402 U.K. establishments in 1984 and 1990
Mishel and Bernstein (1994)	Change in shares of employment of five educational groups regressed against technological proxies	34 industries (manufacturing and nonmanufacturing), 1973–89
Osterman (1986)	Change in employment in response to computer installations 1972 and 1978; 3SLS	20 manufacturing and nonmanufacturing industries
B. Effect of technology on employment:		
Blanchflower, Millward, and Oswald (1991)	Employment growth rate as function of lagged employment (t − 4) and other characteristics of establishment (demand, foreign ownership, union presence, organizational change, financial performance and capacity)	948 British establishments in 1984 with over 24 workers

Indicators of Technical Change	Measures of Labor	Results
Proxies for age of the capital stock	Age, education, gender cells	Older technology negatively correlated with percentage of labor cost devoted to *high-skill workers*
Expenditure on computers, R&D	Nonproduction workers share in total employment and wage bill	Positive correlation between new technology and skills upgrading
High-tech office equipment capital stock	Age, education cells for production and nonproduction workers	Positive correlation between technology measure and share of nonproduction workers
Changes in technology of electronic switching equipment	10 occupational classes of workers	Technology shifts demand in favor of technical and professional employees
R&D expenditure/sales; lagged SPRU innovation counts; introduction of microcomputers	Employment shares of nonmanuals in industry sample; employment shares of six skill groups in plant-level sample	Innovations and R&D positively related to nonmanual share; computers positively related to upgrading only for top skill group
Computing and capital equipment per worker; employment share of scientists and engineers	Proportion of workers with different schooling attainment (five groups); also gross and residual wage inequality	Technology proxies are positively related to educational proportion *but* this effect does not increase in the 1980s
Total amount of main computer memory in industry	Employment of clerks, nondata entry clerks, managers, and others	Computerization associated with falls in employment of clerks and managers; long-run effect for managers significantly smaller than short-run effects
Whether there had been any major introductions of new microelectronic plant and equipment in the previous 3 years	Total establishment employment	Positive and significant effect of advanced technical change on employment growth

Table A1 (*Continued*)

Authors	Methodology	Level of Aggregation
Blanchflower and Burgess (1995)	Change of employment over average of current and lagged employment. Controls include lagged employment ($t - 4$), age, unionization, demand, industry dummies	831 British establishments in 1990; 888 Australian establishments in 1989
Doms, Dunne, and Roberts (1994)	Employment growth regressions and survival probits. Controls for age, capital, size, and productivity.	U.S. plants-level data from Longitudinal Research Database and Survey of Manufacturing Technology, 1987–91
Entorf and Pohlmeier (1991)	Three equation system (exports, innovation, and employment)	2,276 West German firms in 1984
Machin and Wadhwani (1991)	Employment growth rate as function of lagged employment ($t - 4$) and other characteristics of establishment (demand, foreign ownership, union presence, organizational change, financial performance and capacity)	721 British establishments in 1984
Nickell and Kong (1989)	Three equation system (production function, pricing, and product demand). Estimated separately across nine manufacturing industries	45 three-digit British manufacturing industries, 1974–85 panel

NOTE.—SIC = standard industrial classification; SPRU = Science Policy Research Unit; 3SLS = three-stage least squares; the table does not include studies relating technological change to wages or wage bill directly; only selected recent studies have been included; all studies were conducted in U.S. unless *otherwise stated.*

Indicators of Technical Change	Measures of Labor	Results
Whether there had been any major introductions of new plant and equipment in the previous 3 years	Total establishment employment	Positive and significant effect in Britain; positive and weakly significant in Australia
Dummy variables representing numbers of advanced manufacturing technologies present in workplace	Growth of employment in establishment	Positive effects on employment growth
Survey of innovations (dummy variable)	Total employment in firm	Product innovations correlated with significantly higher employment (and exports)
Whether there had been any major introductions of new microelectronic plant and equipment in the previous 3 years	Total establishment employment	Significant and positive correlation with total employment growth
Labor augmenting technical change estimated indirectly as a residual	Total employment	Labor augmenting technical change associated positively with employment in seven out of nine industries

Table A2
Sources and Definitions

Mnemonic	Definition	Source
WAGES	Log firm average wage	DS214, XSC16
EMPLOYMENT	Log firm employment in United Kingdom	DS216, XSC15
INNOVs	Number of firm innovations	SPRU
PRODUCT INNOVs	Number of firm product innovations	SPRU
PROCESS INNOVs	Number of firm process innovations	SPRU
PATENTS	Number of patents granted to firm in the United States	U.S. Patent Office
IND WAGE	Log industry wage	ACoP
UNEMP	Log industry unemployment	*Annual Abstract*
IND DENSITY	Industry union density	Price and Bain (1983)
CAPITAL	Log firm capital—historic value	DS327, 328, 329
IPI	Number of industry innovations produced	SPRU
IUI	Number of industry innovations produced	SPRU

NOTE.—DS = Datastream, XSC = Exstat, ACoP = All industry Census of Production, SPRU = Science Policy Research Unit.

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