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Do firms that create intellectual property also create and sustain more good jobs? Evidence for UK firms, 2000-2006.

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Abstract:

A common assumption in innovation policy circles is that creative and inventive firms will help to sustain employment and wages in high wage countries. The view is that firms in high cost production locations that do not innovate are faced with loss of market share from import competition, so jobs move to producers in developing countries with lower labour costs. Domestic firms are encouraged to innovate, and to obtain intellectual property assets to protect their innovations, so that they can sustain local employment and pay high wages. Policies to subsidise R&D and to encourage intellectual property protection are partly justified on these grounds. Nevertheless the available evidence concerning the employment and wage benefits of such activity is rather sparse.

In this paper we first survey some existing literature on innovation and jobs. We outline arguments for using both patents and trade marks as indicators of innovation. We then construct a large sample of UK firms observed from 2000 to 2006, matching records of patents and trade marks to company data. We begin by estimating a cross section employment growth equation for 2003-2006 to discover if there is any impact of stocks of trade marks acquired in 2000-2003. We then explore in more detail the impact of recent trade mark and patenting activity on the level of employment and the average rate of pay in these firms. We do this using the data as a six year panel, estimating both an employment function and a relative earnings equation at the firm level. Our aim throughout is to identify and calibrate the assumed positive effects that underpin modern innovation policy.

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Introduction

There is a common assumption in innovation policy circles that creative and inventive firms will by these activities help to sustain employment and wages in high wage countries. The view is that firms in high cost production locations that do not innovate are faced with loss of market share from import competition, not just from domestic competitors. If there is little domestic innovation then the consequence of high domestic production costs is that outsourcing and offshoring will take place. In this way jobs move to producers in developing countries where there are lower labour costs. If domestic firms wanted to try to retain jobs in the face of low cost competition from abroad, their only option would be to cut wages.[1]

To counter these forces domestic firms are encouraged to innovate, and to obtain intellectual property assets to protect their innovations. By inventing new techniques and designing novel products, and by retaining some monopoly control over where the new techniques are used and where the novel products are made, they can sustain local employment and continue to pay high wages. Policies to subsidise R&D and to encourage intellectual property protection are partly justified on these grounds. Nevertheless the available evidence concerning the employment and wage benefits of such innovative activity is rather sparse.

In this paper we first summarise some theory concerning how innovation affects the demand for labour. We review some existing literature on innovation and jobs, and we outline arguments for using both patents and trade marks as indicators of innovation. We then describe how we constructed a large sample of UK firms observed from 2000 to 2006, matching records of patents and trade marks to company data including sales, employment and the wage bill.

Our first empirical analysis is the estimation of a simple cross-section employment growth equation for 2003-2006, to discover if there is any impact of stocks of trade marks acquired in 2000-2003. We then explore in more detail the impact of recent trade mark and patenting activity on the level of employment and the average rate of pay in these firms. We do this using the data as a six year panel, estimating both an employment function and a relative earnings equation at the firm level. Our aim throughout is to identify and calibrate the assumed positive effects that underpin modern innovation policy.

Innovation and product demand

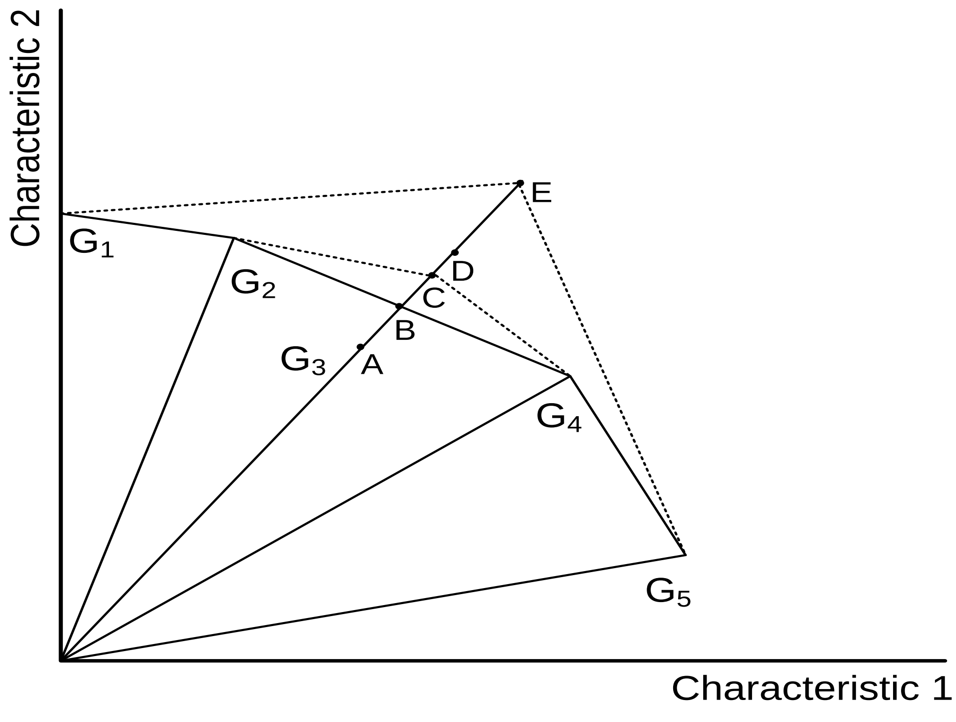
Demand for labour in any firm is a derived demand for the factor input of labour services. This is driven by the demand for the firm's output and by the choice of production techniques within the firm. Our first point of discussion is to summarise how innovation affects these two driving forces of labour demand, namely sales and technology.

[1] This is the prediction of conventional trade theory: with homogeneous factors employed in production, factor price equalisation will result from international trade in standardised goods and services.

Conventional economic literature divides innovation into two types. *Process innovation* is said to occur when a firm invents a more efficient element of a production process, leading to lower costs per unit for an existing product type. *Product innovation* is the design and delivery of novel products that will attract customers to the firm. This again can be split into two types: drastic or *radical innovation* being used to describe products that achieve very significant departures from earlier ones, and *incremental innovation* describing products that build on existing product types. Even here the discrimination continues with the term *horizontal differentiation* being attached to a new variety of an existing product which incorporates a recombination of existing characteristics and *vertical differentiation* indicating a higher quality of product with substantially superior characteristics.

While all these distinctions have their uses, particularly in showing the diversity of innovation, we can actually incorporate all these innovation types into one framework by applying the Lancaster model of consumer behaviour (Lancaster, 1966 and 1971). This model shows that firms are engaged in a competition involving product price and product quality simultaneously. In the Lancaster model consumers are not wedded to particular products. Rather it is the case that consumers value the characteristics and services derived from products. In this framework we define consumer choice as utility maximisation in characteristics space, where particular goods and services are intermediate inputs that deliver sets of characteristics either singly or in combination. When purchasing goods or services the consumer maximises their satisfaction by choosing the products that supply their most valued amount of product characteristics for a given expenditure. We can demonstrate within this framework that process and product innovations are two sides of the same coin, as both bring about new possibilities for purchases that can improve customer satisfaction and switch demand towards innovative producers.

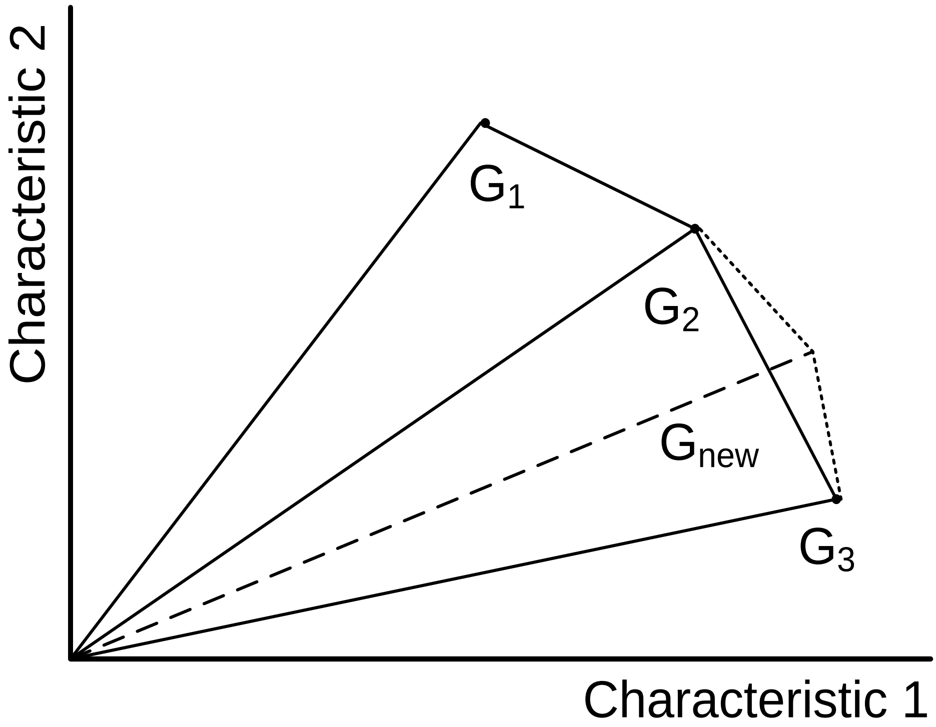
Figure 1 Cost reduction of an existing variety due to process innovation



In Figure 1, drawn from Lancaster (1966), the axes measure the amounts of two characteristics desired by consumers. In this space each ray represents one product and the slope of the ray reflects its embodied ratio of characteristics. Given that prices of products are fixed we can draw the efficiency frontier for the consumer, which joins points representing equal expenditure on the given products. To maximise their utility for a given expenditure, consumers may opt to buy only one product (thus being at a corner solution on the segmented efficiency frontier) or a combination of products (an interior point on one segment of the frontier). What they choose to purchase depends on their tastes which embody their implicit valuation of the two characteristics.

Suppose there is an existing producer of product G3 who achieves a process innovation that could permit this firm to make a cost reduction. As the price falls the point of possible consumption moves away from the origin on ray G3. At price A product G3 is uncompetitive, at B just competitive with existing producers, but at the lower price indicated by C the efficiency frontier is extended. For consumers that now decide to purchase G3 there are utility gains. If the price were to fall to the level indicated at E, then G3 displaces G2 and G4 entirely, as linear combinations of G1 or G5 with G3 are more cost effective at delivering the desired characteristics than the attainable amounts of G2 or G4.

Figure 2 **Introduction of a new variety due to product innovation**



In Figure 2 the innovation is of a new product that introduces a different combination of the two characteristics. If the ray representing G_{new} is within the existing range of products and the constant expenditure is not too far from the existing frontier we could term this an incremental horizontal innovation. Provided it is not priced too highly it will extend the efficiency frontier. This will displace some purchases of the adjacent product types and increase customer satisfaction. As before, if price drops sharply then some adjacent types may become redundant. This same diagram could also illustrate a product innovation that was radical and vertically differentiated. Suppose that the length of the dotted line representing G_{new} was much longer than illustrated and/or lay to the left of G1 or to the right of G3 so that it had more drastic effects on the existing efficiency frontier. This product introduction would have more significant effects on consumer purchases. As in Figure 1 the impact of the product on patterns of demand depends on both its quality and price.

The above analysis indicates the expected positive relationship between innovation and product sales. Now we turn to the question of how this might translate into more jobs and better worker remuneration.

Innovation and jobs

Process innovation is often seen as labour saving due to the substitution of modern capital equipment for workers. The is especially true in manufacturing due to automation of factories, but has also been seen in services, such as banking and retailing, where the use of automated teller machines and on-line services has led to job losses. These negative effects on demand for labour may be offset by the countervailing effect of market expansion. This occurs when the cost reduction from process innovation is partly or fully passed through into lower prices, allowing the innovative firm's market share to expand.

As seen above, a product innovation will expand sales and thus be job-creating if the new item is priced so that it extends Lancaster efficiency frontier. How much sales rise will depend on whether the new product enters a dense part of the utility distribution. Often both process and product innovation will occur simultaneously, as the change of techniques arising from process innovation permits the design of novel varieties and radical innovations. Regarding the demand for labour, even if there are more jobs on offer the composition of employment by skill may change. This is termed skill-biased technological change, which occurs when standard production jobs are lost to automatic processes, but more skilled designers and researchers are recruited to push forward product innovations based on the new technology. Thus in total the net effect of innovation on jobs in a given sector, or in the whole economy, is not predictable from theory, but may well be positive if the job-creating forces outweigh the job-destroying ones; even so the skill mix is very likely to change in favour of higher skill levels.

Innovation and pay

As well as examining changes in employment in innovative firms we shall be analysing average annual pay per employee within the firm. Why would we expect average pay to be higher in innovative firms?

There are several possible routes for a wage rise. First, innovative firms will gain a rise in profitability, either from process innovation leading to reduced costs, or due to the novelty of their product innovations permitting them to raise prices. As a result they may be willing to share these temporary rents from market leadership with workers and so hourly rates will increase. Second, where there is a net increase in demand for labour, this may be met by increasing the hours worked by existing staff, leading to arise in annual pay per worker. Third the changing skill structure of the firm towards employing more highly skilled workers will lead to a rise in average rates of pay across the firm as these workers cost more than those made redundant by the new technology.

Indicators of innovation

Moving towards our empirical analysis we need to construct some useful indicators of innovation. In the early literature on the value of innovation there has been frequent use of the level of R&D spending in the firm to proxy investment in intangible assets. There are three significant difficulties with this measure. First R&D spending is an input measure, so cannot convey information about the level and precise timing of the success of the R&D programme in creating new products and processes. Second, this variable tends to be quite smooth over time for a given firm, whereas its output of innovative techniques and products is lumpy, or discontinuous. Third, many firms do not report R&D separately in their company accounts.

If we are willing to assume that firms register some form of intellectual property whenever they make a process or product innovation, in order to protect their ownership of the novelty they have created, then we can use IP to signal the incidence of innovation. Patents taken out by the firm certainly offer an output measure for the R&D process. This variable will record some significant innovations due to the requirements of novelty and non-obviousness for the grant of a patent. Its deficiency is that it is highly concentrated in goods sectors as many significant innovations in services provision are not items that can be patented in the UK and Europe due to the absence of such IP rights as business methods patents and software patents.[2] Another difficulty with patents is their timing can precede the launch of the derivative products by an unknown, variable lead time. Two important missing elements in the spectrum of IP types are those of copyright measures (for which there is no registration) and design rights, which although registered are generally neglected in econometric modelling. Our response to this incomplete pattern of measures of IP has been to adopt counts of trade marks as an indicator of innovation.

Three economic functions of trade marks have been set out in the economics and law literature. In law the unique nature of the registered mark gives a guarantee of the origin of the product. This allows the market to function with greater information efficiency for customers, who do not waste time and money searching for products to fit their specific needs (see Landes and Posner, 1987). While this is a useful interpretation of the usefulness of the stock of well-known trade marks, we can draw on a second interpretation here to get closer to innovation.

This view argues that the registration of a new trade mark occurs when a new product is brought to market, so it acts as a signal of innovation. There is support for this hypothesis in the paper by Mendonca et al., 2004, who present evidence of a positive correlation between innovation and trade mark activity across a number of European countries. A further point that supports the use of trade mark registrations to proxy innovation is that, as already noted, very few service sector firms engage in formal R&D or report patents, yet innovation in services is frequent and service industries employ a far larger share of employment than does manufacturing. As documented in Rogers, et al. 2007, firms in all sectors of the economy and of all sizes can be active in registering trade marks.

A third view is less sympathetic to the idea of trade marks as signals of genuine innovation. The registration of a new product name or sign can be the start of a process of building a strong new

[2] It is also well known that the value of different patents is extremely heterogeneous so that simple counts can be misleading indicators of intangible assets. The use of citation weighted values goes part way towards rectifying this problem, but for short samples like ours it is not possible to construct these.

brand using a range of advertising and marketing techniques. This can take place when there is little by way of novelty in the product. This approach has been emphasized by some industrial organisation literature (see for example the debate in Lopes and Duguid, 2010), which sees trade mark applications as anti-competitive activity that is not always justified by any real product improvement. While we can control for this sort of activity by including recent expenditure on advertising and marketing in our empirical analysis, there is a danger here of minimizing the observed impact of a genuine innovation correlated with an application for a trade mark. This is because innovative firms will of course engage in advertising their new products at the same time as less innovative firms will be advertising their repackaged existing products.

Existing empirical literature on innovation and jobs

If direct survey data on firms' innovative experience is available, then the need for innovation proxies is of course minimised. A recent comparative paper for the UK, France, Germany and Spain uses Community Innovation Survey data on reported innovation without reference to any IP variables (see Harrison et al. 2008). In this study the database draws on the third survey (CIS3) for these four countries, analysed separately but in parallel, and the coverage of firms includes services as well as manufacturing firms. The data provides only a cross-section of firm innovation and growth, as they have only two observations per country for the key variables of firm level employment and sales (in 1998 and 2000). They decompose actual employment growth for each firm into four components (reported as two year average effects in each country for manufacturing and services and tabulated in Table 5 of Harrison et al. 2008):

a) trend productivity within the industry in the production of old products;
b) gross productivity effect of process innovation in the firm in the production of existing products;
c) output growth of old products for firms not innovating;
d) net contribution of product innovation, allowing for any substitution of new products for older ones.

The results were:

a) trend productivity was most often labour-saving, so negative for labour demand;
b) process innovation showed some positives and some negative for jobs, but with very small impacts;
c) output growth was large and positive for jobs;
d) product innovation was also strongly positive for jobs, although mostly smaller than c).

Product innovation consistently contributed between 2.5% and 4% per annum to employment growth in manufacturing and services. The effects of process innovation were not always negative, and even when they were, their magnitude was less than 0.3% per annum in both sectors for all four countries. Hence innovation appears to have been an extremely important contributor to European job growth at the end of the 1990s.

Another methodology that has been used to evaluate the impact of innovation on jobs is to estimate firm-level employment functions. The first UK paper on this topic was by Van Reenen (1997), who analysed a short panel of manufacturing firms observed in 1977-82. Innovation was proxied using the Sussex SPRU counts of innovations in firms in the post war era and also their US patents. The SPRU data was generated by continuous sampling of experts concerning the major innovations in their sector, so it represents genuinely novel innovation, both process and product, which could be distinguished in the data. Given the SPRU data had a longer time span than the firm database, the author was able to examine long lags in the impact of innovation and also explore interactions between firms.

Van Reenen (1997) estimated a demand for labour function that was derived using the cost minimising approach to producing a given output.[3] He found considerable positive impact of innovation on firm employment, increasing for up to six years, but no impact of US patents. Product innovations were much more positive and significant than process innovation, which when entered separately produced insignificant effects. There was no evidence of inter-firm spillovers within the industry and the author posits that this is because any positive diffusion of knowledge from other firms is outweighed by rivalry.

A second paper focusing on UK firms, but the first using UK IP variables including both patents and trade marks is that by Greenhalgh, Longland and Bosworth (2001). These authors analysed a panel of large UK production firms (so none in services) observed during 1987-94. Innovation was proxied using R&D, UK patent publications (including filings via the EPO), US patents and UK trade marks, with some lags on these variables permitting the use of stock variables on the assumption of rapid depreciation. Employment was specified (following the cost-minimising model) as depending on recent firm sales, industry wages, capital and raw materials costs, together with the variables reflecting innovation.

In their employment function, which included firm fixed effects to control for persistent differences between firms, the authors found positive impacts of R&D, and of UK patents, but no further impact of EPO or US patents, nor of recent trade marks. For separated samples of high-tech and low-tech production firms the results differed, with R&D showing more impact in high-tech firms and UK patents more impact in low-tech firms. A separate exercise was conducted using the saved values of the firm fixed effects (which are the persistent variations in employment levels across firms). These showed positive impact of activity in UK and US patents and in UK trade marks; thus IP active firms were shown to be persistently different in cross-section from non-IP active firms during 1987-1994.

As well as the impact on jobs we are also interested in the effect of innovation on wages. Another paper by Van Reenen (1996) using his sample of UK firms in the late 1970s, investigated whether firms that were innovative also paid higher wages to their workers. He modeled the economic rents (excess returns above minimum profits for survival) accruing to firms in two ways, looking both at their short-term profitability and at their longer term expected profitability, as assessed by the stock market when valuing company shares. His findings showed innovation to be a significant determinant of rents and also that around 20-30% of these rents were passed through to workers in the form of higher wages.

[3] Even so, instead of including output in the equation he used the parallel capital demand equation to substitute for output. This meant that his labour demand equation includes capital, which seems likely to introduce possible bias if there are correlated errors in variables, as capital and labour services are chosen simultaneously in the standard labour demand model in response to their relative prices.

In an analysis of their sample of UK production firms in the late 80s and early 90s, Greenhalgh and Longland (2001) estimated a relative wage function to compare innovative firms with others in their industry. The findings were that R&D and trade marks were associated with higher wages than average, but patents were not significant determinants of relative wages. A number of interpretations are compatible with these findings: first, the acknowledged lag between patents and delivery of innovative products to the market ; second, the fact that trade marks may be closely related to product innovation, while patents could be more divided between product and process innovations, with the latter creating ambiguous effects on the need to reward and retain workers.

The Database

For the empirical work reported below we constructed an integrated database of company records and new flows of intellectual property. The starting point was the Office of National Statistics' Annual Respondent Database (ARD2) for the years 2000-2006 (Robjohns, 2006). The ARD is not a population database as it has a sampling design for smaller firms. For the period under analysis the objective of the ONS was to sample micro firms (with 1-9 employees) at a 25% rate, firms with 10-99 employees at 50%, firms with 100-249 employees at either 100% or 50% depending on the industry, and larger firms (250 or more employees) at 100%. The result is that large firms and some medium sized firms are more likely to be in the panel of data as these are observed in all successive years, whereas some medium and all smaller firms are sampled and their records are thus discontinuous.

Prior to gaining access to this business data we had already searched using firm names to count trade marks and patents from 2000-2006. The coverage of these IP variables was all the UK trade marks and European Community (OHIM) trade marks and all the UK patents and European Patent Office patents relating to named firms by year. Within our in-house database (OFLIP), which is described in detail in Helmers et al. (2011) we had matched company data from FAME to these IP activities for the whole population of live firms in UK. However for the purposes of the current analysis, the ARD had more variables than FAME for each of its sample firms, especially in terms of its coverage of employment. It also contained the ownership structure for complex firms with parents and subsidiaries. The compromise was to match our IP counts to the ARD sample of companies to create an enhanced ARD panel of firms from 2000-2006.

An analysis of trade marks and growth:

To examine whether short term employment growth is related to recent trade mark activity, as a first test of the usefulness of the trade mark measure of innovation, we estimated a simple growth equation. The model permits us to test Gibrat's law, which hypothesises that firm growth is independent of initial firm size.[4] For this purpose we selected only those firms with continuous data in all years. The data was then used as a cross section of observations of growth in period t, where *t* is the period 2003-2006, analysed in relation to initial employment and to stocks of trade marks and advertising at the start of this period. Thus for the definition of the lagged variables *t-1* is the period 2000-2003 for these 'stocks'. The equation for estimation was:

$$g_{it} = \beta_1 l_{it-1} + \beta_2 TM_{it-1} + \beta_3 A_{it-1} + \beta_4 X_{it-1} \qquad (1)$$

[4] For reviews if this literature concerning the growth of firms see Audrestch et al. (2004) and also Hart and Oulton (1996 and 1999).

- *g* is annual growth of employment in second period
- *l* is end of first period employment level
- TM is either the incidence (dummy), or the count (stock) of trade marks during t-1
- A is cumulative stock of advertising & marketing expenditure during t-1
- Stocks of TM and A are depreciated at 15% p.a.
- X is a vector of control variables
- A full set of sector dummies was also included
- Continuous variables are in natural logs except for trade mark stock
- Mean of g = 0.07   SD = 0.25   Median of g = 0.016

Table 1   Growth of employment (2003-2006) regressions

	(1)	(2)	(3)
log employ (2003)	-0.0334***	-0.0442***	-0.0444***
	(0.00)	(0.00)	(0.00)
TM dummy (2000-2003)	0.0614***		
	(0.01)		
TM stock (2003)		0.0005***	0.0014***
		(0.01)	(0.01)
Log Adv Stock (2003)		0.0135***	0.0138***
		(0.00)	(0.00)
TM stock x log Adv			-0.0001**
			(0.00)
Log age (2003)	-0.0502***	-0.0521***	-0.0522***
	(0.01)	(0.01)	(0.01)
Industry TMs int.	-0.0516***	-0.0791***	-0.0795***
	(0.02)	(0.02)	(0.02)
Industry patent int.	-0.0706***	-0.0632***	-0.0643***
	(0.02)	(0.02)	(0.02)
Exporter (2003)	-0.0238***	-0.0302***	-0.0306***
	(0.01)	(0.01)	(0.01)
Foreign (2003)	0.0003	-0.0009	-0.0008
	(0.06)	(0.01)	(0.01)
Constant	0.3052***	0.3249***	0.3252***
	(0.03)	(0.03)	(0.03)
Observations	8470	8470	8470
R-squared	0.08	0.09	0.09

Notes: Dependent variable = growth of employment. Robust standard errors are in parentheses. Significance is indicated as *** p<0.01, ** p<0.05, * p<0.1. Sector dummies also included (always statistically significant as a group at the 1% level). Source: Greenhalgh et al. 2011, Table 23. Means and standard deviations of these regression variables are given in Appendix Table A3.

The findings from this analysis are presented in Table 1. They begin by rejecting Gibrat's law, as the significant negative coefficient on initial employment means that smaller firms grow faster than larger firms. This coefficient implies that a 10% increase in firm size (a 0.1 change in log value) is associated with a 0.3% fall in its annual growth rate.

Within the list of control variables we include the firm's age (negative, so mature firms grow more slowly), whether it has exporter status (also negative, but this is rather counterintuitive) and foreign ownership (no effect). The extent of the innovative environment in which the firm operates is measured by the industry levels of trade mark and patent intensity. Higher industry values depress growth in the single firm, reflecting the effects of a more intense Schumpeterian competitive environment.

We now turn to the results for trade mark and advertising activities. As noted above we are unsure whether or not advertising should be controlled for in a regression to assess innovation proxied by trade marks, since a considerable amount of advertising may be required for the announcement and marketing of innovative products. Hence we show results for alternative specifications first without and then with advertising included.

Table 1 col. 1 reveals that firms that were trade marking between 2000 and 2003 show a 6% growth premium (when advertising is not included) in comparison with firms that registered no trade marks. This is a large impact in relation to mean growth of around 7%. In col.2 when advertising and TM stocks are jointly included both are significantly positive so the effect of trade mark activity is not eliminated but its size is reduced, as expected given the correlation between these variables. Using the second specification shows that an increase of 10 TMs (around half of one standard deviation) in last period stock leads to extra growth of 0.5% per annum.[5] To attain the same increase in growth from a rise in advertising stock would require a rise of 37% in advertising and marketing expenditure.

Thus advertising looks quite effective but does it need a set of trade marks as a flag around which to organize the campaign? We might expect that if advertising and trade marks are reinforcing influences for building strong brands then their interaction would show a further positive impact. However as shown in Table 1 col.3, the coefficient on the advertising and trade mark interaction variable is negative. Thus they are substitutes, not complements, in the promotion of firm growth and this indicates the existence of limited resources in the firm that can be devoted to promoting older products or to developing new ones.

Employment in firms – the choice of input factors

The specification of an employment function follows the approach of Van Reenen (1997) and Greenhalgh et al. (2001) by reflecting the derived demand for labour in firms that are using cost-

[5] However this is quite a large increment to trade mark activity in this short four year period in which stocks are accumulated, as the mean of trade mark stock is 2.7. The large standard deviation of 19.2 arises because stocks are highly skewed.

minimization for producing a given output.[6] This basic employment equation, which reflects the fact that derived demand is a function of output and factor input costs, is given by:

$$l_{it} = \alpha_0 + \alpha_1 s_{it} + \alpha_2 w_{jt} + \alpha_3 c_t + \alpha_4 m_{jt} + e_{it} \qquad (2)$$

where:

- *l* is firm employment
- *s* is the firm's current sales (turnover)
- w_j is the industry wage (median hourly earnings of full time workers excluding overtime)
- *c* is the (country) cost of capital (measured by the real interest rate)
- m is the industry cost of materials
- all variables are in natural logs

The main input price variables (wages, materials costs, interest rates) were those prevailing in the industry or year, so were not firm specific. Using industry level wages avoids problem of some firm-specific costs being endogenous to whether or not the firm is innovating (e.g. it is doing R&D, so hires expensive researchers). Industry input costs were obtained from government figures.

To this specification we can add variables reflecting trade marks and patents so that the equation for estimation is:

$$l_{it} = \alpha_0 + \alpha_1 s_{it} + \alpha_2 w_{jt} + \alpha_3 c_t + \alpha_4 m_{jt} + \alpha_5 P_{it-1} + \alpha_6 T_{it-1} + e_{it} \qquad (3)$$

where *P* and *T* refer to the firm's patents and trademark activity in the previous year. These are measured as dummy variables, reflecting any such activity in the firm, and as intensities, reflecting the rate of innovation activity relative to the size of the firm. In this equation, unlike that for firm growth, we do not include advertising as a proxy for intangible assets, because we already have current sales in the equation and this captures much of the effect of recent advertising.

What does IP capture in this regression? If firms are anticipating a rise in orders due to innovation, then their decision to hire will depend on future sales not just current gross output. The level of expected future sales is unobserved, but as we use current sales as our scale variable, this leaves any residual of expected change in sales due to innovation to be picked up by these variables. Innovation variables will also pick up firm-specific variation in the employment intensity of producing a given level of output, which is influenced by their choice of technology and the general productivity of their labour input. A priori, the net sign of the total effect of innovation on employment is not predictable as process/productivity and product/sales effects could be offsetting, so it depends which is largest.

The first results for the employment function are presented in Table 2 in which the trademark and patent variables are measured using dummy variables for any such activity. In this analysis the entire

[6] The same equation can be derived by maximising the output produced from a given cost expended on inputs.

volume of available observations for firms and years has been pooled, so that within the dataset comparisons are being made both between different firms in all years and within the same firm in different years. Table 2 col.1 contains the basic derived demand for labour. The coefficients on each variable look plausible: first, the sales elasticity is positive but less than one, indicating that as firms grow they do not enlarge their UK workforce at the same rate. The wage elasticity is -0.7 which is in the range of values indicated by many other studies. The negative sign on the real interest rate indicates that labour and capital are complements in production, whereas labour and materials are substitutes.

Table 2 Pooled OLS employment regressions with IP dummies

	(1)	(2)	(3)
Sales	0.4811***	0.4734***	0.4733***
	(0.0105)	(0.0106)	(0.0106)
Industry real wage	- 0.7205***	- 0.7042***	- 0.7048***
	(0.0498)	(0.0493)	(0.0494)
Industry materials costs	0.0795***	0.0777***	0.0776***
	(0.0072)	(0.0071)	(0.0072)
Real interest rate	- 4.5779***	- 4.6879***	- 4.6908***
	(0.6065)	(0.6049)	(0.6053)
TM dummy (t-1)		0.1977***	0.1970***
		(0.0274)	(0.0274)
Patent dummy (t-1)			0.0103
			(0.0491)
Constant	6.6968***	6.8401***	6.8448***
	(0.6443)	(0.6433)	(0.6442)
Observations	34969	34969	34969
R-squared	0.48	0.48	0.48

Notes: Dependent variable is log of employment in the firm. Robust standard errors are in parentheses. Significance is indicated as *** p<0.01, ** p<0.05, * p<0.1. Source: Greenhalgh et al. 2011, Table 17. Means and standard deviations of these regression variables are given in Appendix Table A4.

Table 2 col.2 shows how much more labour intensive are firms that have recently been trade mark active. The coefficient on trade mark activity implies that these firms have a 20% higher level of employment for a given level of sales. Given the pooling of the cross section and the time series here, it is likely that that this figure reflects differences in labour intensity between firms that regularly use trade marks and those that do not. We would expect that the process of generating new varieties of products and marketing them as they are launched would give rise to higher levels of employment. Any labour savings from new process innovation appear to be strongly dominated by the job creating effects of product innovation. Even so, in Table 2 col. 3, when we introduce the patent dummy variable in concert with the trade marks dummy, its coefficient implies no significant further impact on jobs in this simplified specification; however this picture is changed below when we look at IP intensities.

In Table 3 the model of employment in relation to trade mark and patent activity is augmented by including first the level, and then also the squared value, of trade mark intensity in the firm. Before examining these results we note that, in an earlier study of UK patents and trade marks, Rogers et al. (2007) showed that firms do not generally increase their numbers of patents and trade marks pro rata with size. Thus both patent and trade mark intensity decrease on average with firm size and any relationship between employment and intensity can be inverted when interpreting it in relation to firm size.

In Table 3 cols. 1 and 2, the addition of trade mark and patent intensity gives rise to coefficients that are negative, revealing that the employment effects of trademarking are bigger in larger firms. For both these variables the fullest specification is that of the quadratic function in col. 3, which shows very similar patterns of variation in employment with each type of IP intensity. There is a positive effect of doing either patenting or trademarking that declines with intensity (increases with size of firm), but with a non-linear slope (due to the positive coefficient of the squared value of incidence).[7] In the case of patents, the insignificant finding in Table 2 above is explained by the inability of the simple dummy to parameterise this quadratic function.

Table 3 Pooled OLS employment regressions with IP intensities

	(1)	(2)	(3)
Sales	0.4732***	0.4727***	0.4705***
	(0.0106)	(0.0106)	(0.0106)
Industry real wage	- 0.7041***	- 0.7018***	- 0.6934***
	(0.0493)	(0.0494)	(0.0493)
Industry materials costs	0.0777***	0.0770***	0.0766***
	(0.0071)	(0.0072)	(0.0071)
Real interest rate	- 4.6804***	- 4.7530***	- 4.6447***
	(0.6044)	(0.6047)	(0.6045)
TM dummy (t-1)	0.1994***	0.1995***	0.2515***
	(0.0277)	(0.0276)	(0.0291)
Trade mark intensity (t-1)	-0.0010	- 0.0008	- 0.0443***
	(0.0033)	(0.0032)	(0.0117)
Trade mark intensity (t-1) squared			0.0001***
			(0.0000)
Patent dummy (t-1)		0.1436***	0.2529***
		(0.0543)	(0.0614)
Patent intensity (t-1)		- 0.1298***	- 0.3079***
		(0.0304)	(0.0507)
Patent intensity (t-1) squared			0.0143***
			(0.0039)
Constant	6.8333***	6.8401***	6.8067***
	(0.6427)	(0.6433)	(0.6428)
Observations	34969	34969	34969
R-squared	0.48	0.48	0.48

Notes: Dependent variable is log of employment in the firm. Robust standard errors are in parentheses. Significance is indicated as *** p<0.01, ** p<0.05, * p<0.1. Source: Greenhalgh et al. 2011, Table 18. Means and standard deviations of these regression variables are given in Appendix Table A4.

In Table 4 the estimation method is changed to a fixed effect specification. In this analysis the use of what are effectively firm-specific constants eliminates employment differences between firms that are associated with persistent differences in their patent or TM activity, as these get absorbed by the fixed effect together with other permanent differences in firm characteristics. The result is that the coefficients are being estimated from the changes that occur within firms as the explanatory variables, including IP activity, change through time. As is often the case within a short panel this makes for fewer well-determined coefficients. As a start we notice that the wages variable is now perversely signed, showing elements of a supply relationship to the firm (in that higher wages and employment go together).

[7] For both patent and trademark intensity the minimum value of these quadratic functions is well outside the range of observations in the sample, so in neither case is there an eventual upturn.

Table 4 Fixed effects employment regressions with IP dummies

	(1)	(2)	(3)
Sales	0.0914***	0.0913***	0.0913***
	(0.0080)	(0.0080)	(0.0080)
Industry real wage	0.3306***	0.3319***	0.3319***
	(0.0557)	(0.0557)	(0.0557)
Industry materials costs	0.0252***	0.0252***	0.0252***
	(0.0044)	(0.0044)	(0.0044)
Real interest rate	- 2.0376***	- 2.0445***	- 2.0454***
	(0.2977)	(0.2975)	(0.2976)
TM dummy (t-1)		0.0308***	0.0307***
		(0.0087)	(0.0087)
Patent dummy (t-1)			0.0053
			(0.0158)
Constant	5.9155***	5.9176***	5.9186***
	(0.3525)	(0.3523)	(0.3523)
Observations	34969	34969	34969
No. of firms (groups)	7038	7038	7038
R-squared (within)	0.06	0.06	0.06
R-squared (between)	0.40	0.40	0.40

Notes: Dependent variable is log of employment in the firm. Robust standard errors are in parentheses. Significance is indicated as *** p<0.01, ** p<0.05, * p<0.1. Source: Greenhalgh et al. 2011, Table 19. Means and standard deviations of these regression variables are given in Appendix Table A4.

Comparing the coefficients in Table 4 cols. 2 and 3 with their counterparts from Table 2 shows that the marginal impact of recent TM activity on employment, for firms that did not trade mark in the previous year, is now just a 3% increase, while the impact of new patenting activity in a given year is once again insignificant.[8] We see these as compatible results - it is unlikely that a firm would engage 20% more workers on the basis of a single recent innovation signalled by a new trademark, but it is more realistic to expect a small rise in employment of 3% to help with the product launch. At the same time, those firms in the cross section that are persistently innovating in each year would be likely to employ considerably more workers than firms that do no innovation. The former will engage workers to design and market its evolving set of novel products, while the latter will be forced to slim its workforce to remain competitive on price as a low-cost provider of staple products.

Rewarding workers – the sharing of rents

In specifying a wage equation to investigate the possible impact of innovation on wages, we follow the approach developed in Greenhalgh and Longland (2001) which is to explore the firm's relative wage compared to others within the industry. This permits us to take account of considerably fewer variables than would be needed to account for variation in the level of firm wages within the economy as a whole. Within this framework we hope to see whether IP active firms are sharing any profits with their workers. We include a measure of advertising and marketing to control for situations where the firm is running a very strong marketing campaign to promote market share

[8] Specifications of the fixed effect model for employment estimated with IP intensity variables designed to mimic Table 3 yielded no significant coefficients so are not shown here.

with brands offering few innovative characteristics. We also control for firm size as this is known to affect pay even within an industry. The basic relative wage equation is thus given by:

$$p_{it} = \alpha_0 + \alpha_1 w_{jt} + \alpha_2 z + \alpha_3 a_{it-1} + e_{it} \qquad (4)$$

where:

- p_i is the average earnings in the firm
- w_j is the industry wage (median hourly earnings of full time workers excluding overtime)
- z is a firm size indicator (dummy variable)
- a is recent advertising expenditure

and all continuous variables are in natural logs.

As with the employment equation, we then augment the equation with IP variables:

$$p_{it} = \alpha_0 + \alpha_1 w_{jt} + \alpha_2 z + \alpha_3 a_{it-1} + \alpha_4 P_{it-1} + \alpha_5 T_{it-1} + e_{it} \qquad (5)$$

The results for these equations are shown in Table 5, using IP dummy variables, and in Table 6, where IP intensities are included. Both Table 5 and 6 report results for the pooled sample using OLS.[9]

Table 5 Pooled OLS firm wage regressions with IP dummies

	(1)	(2)	(3)
Industry nominal wage	0.8438***	0.8444***	0.8439***
	(0.0044)	(0.0044)	(0.0044)
Small firm dummy	0.0048***	0.0047***	0.0047***
	(0.0018)	(0.0018)	(0.0018)
Large firm dummy	0.0011	0.0008	0.0008
	(0.0013)	(0.0013)	(0.0013)
Advertising (t-1)	0.0008***	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)
TM dummy (t-1)		0.0072***	0.0062***
		(0.0011)	(0.0011)
Patent dummy (t-1)			0.0132***
			(0.0024)
Constant	8.0289***	8.0279***	8.0290***
	(0.0097)	(0.0097)	(0.0097)
Observations	34971	34971	34971
R-squared	0.89	0.89	0.89

Notes: the dependent variable is log of firm annual earnings per employee. Robust standard errors are in parentheses. Significance is indicated as *** p<0.01, ** p<0.05, * p<0.1. Source: Greenhalgh et al. 2011, Table 20. Means and standard deviations of these regression variables are given in Appendix Table A4.

[9] Fixed effect regressions are not shown as no IP variables were significant in wage regressions whether measured as dummy variable or intensities.

As noted above (on page 5) since individual annual pay is hourly wage x hours per year, and the average pay in the firm is the average across all workers, there are several reasons why average pay could rise within a firm following innovation. Thus pay rises if any of the following happen: the hourly wage increases for a worker of given skill level (sharing of the profits of innovation); workers undertake more hours per year (more overtime, or a rise in the full time to part time worker ratio); the composition of the workforce changes to include more skilled workers.

In the basic wage specification (Table 5 col.1) as expected the industry wage is a strong determinant of firm wages. However there is a surprise in that, in this sample, smaller firms pay above medium and large firms by 0.5% per worker per annum. We noted above that there was a greater constraint on the sample selection of small firms for the ARD survey than for medium and large firms. There was a further constraint imposed by us in that, for these panel regressions, firms had to have data for at least three years continuously. For these reasons the small firms in the regression sample might not be typical of all such firms in the economy. One possible interpretation is that these small firms may be demanding longer hours per worker or employing a different mix of workers with more skills.

Table 6 Pooled OLS wage regressions with IP intensities

	(1)	(2)	(3)
Industry nominal wage	0.8444***	0.8439***	0.8439***
	(0.0044)	(0.0044)	(0.0044)
Small firm dummy	0.0047***	0.0047***	0.0047***
	(0.0018)	(0.0018)	(0.0018)
Large firm dummy	0.0008	0.0008	0.0009
	(0.0013)	(0.0013)	(0.0013)
Advertising (t-1)	0.0005**	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)
TM dummy (t-1)	0.0074***	0.0064***	0.0062***
	(0.0011)	(0.0011)	(0.0011)
Trade mark intensity (t-1)	-0.0001***	- 0.0001***	0.0000
	(0.0000)	(0.0000)	(0.0002)
Trade mark intensity (t-1) squared			- 0.0000
			(0.0000)
Patent dummy (t-1)		0.0114***	0.0085**
		(0.0029)	(0.0034)
Patent intensity (t-1)		0.0018**	0.0064***
		(0.0008)	(0.0018)
Patent intensity (t-1) squared			- 0.0004***
			(0.0001)
Constant	8.0279***	8.0291***	8.0290***
	(0.0097)	(0.0096)	(0.0096)
Observations	34971	34971	34971
R-squared	0.88	0.89	0.89

Notes: the dependent variable is log of firm annual earnings per employee. Robust standard errors are in parentheses. Significance is indicated as *** p<0.01, ** p<0.05, * p<0.1. Source: Greenhalgh et al. 2011, Table 21. Means and standard deviations of these regression variables are given in Appendix Table A4.

Table 5 col.2 shows that being trade mark active in a given year leads to a pay premium of 0.7% in the next year. This result is only marginally reduced by the inclusion of the patent dummy (in col.3), which indicates that being patent active leads to pay premium of 1.3% in the next year. Taken together, these findings suggest that, if workforce composition is unchanged, then workers in firms that acquire both types of IP assets are subsequently given a pay rise of almost 2%.

In Table 6 we examine the impact of changing IP intensity. For trade marks there is almost no impact, as the negative coefficient is extremely small even though significant. However the sign of the effect is consistent with the results for employment in that wage gains are slightly bigger in the large firms which have lower TM intensity. For patent intensity the sign is reversed and the slope is considerably larger; also both the linear and quadratic models show this increasing wage effect as patent intensity rises. This raises the question again as to whether the main impact of firms searching for patents is a change in the proportion of highly skilled workers, which is showing up most significantly in the smaller firms that have higher patent intensity.

In both Tables 5 and 6, recent advertising expenditure is associated with higher pay suggesting the possibility that increased market power does lead to some rent sharing. However the coefficients are extremely small in all regressions. As an illustration, a rise in advertising of one standard deviation, which is 70% of the mean, produces only a percentage rise in wages of 0.2%.

Summing up

From our review of some early literature on the impact of intellectual property on employment and wages, we saw evidence of positive effects of intellectual property on both employment and wages. Having conducted new empirical analysis of employment growth, workforce size and average pay using a large firm-level database, we conclude that the answer to the question in the title of this paper is –Yes, firms that are active in acquiring patents and trade marks are sustaining larger workforces through time and paying higher average wages than inactive firms.

Taking the results as a whole, we also feel confident that our use of both patents and trade marks to proxy innovation has been worthwhile. The effect of trade marks extends beyond the impact of being a vehicle for advertising and plays a further positive role, remaining significant even when we include advertising variables in the analysis. This evidence supports the view that firms signal their innovations by registering new product names and/or logos close to the time when they launch new products.

In the determination of employment, the effect of being trade mark active is more significant than that of being patent active. As noted in earlier work (Rogers et al. 2007) and confirmed in this database, the proportions of firms that acquire a trade mark in each year are very low: below 2% for the smallest firms, rising to 5% of medium sized and 13% of large firms. The proportions of firms gaining a patent are considerably lower in each case, due to the higher degree of novelty required for patents. Raising the proportion of firms that achieve the status of being trade mark active as they offer a new variety or quality of product or service to the market seems a worthwhile objective for innovation policy in the current era of high unemployment.

Appendix: Descriptive statistics for sample and regression variables

Table A1 Trade marking firms and propensities, by year and firm size

	Numbers of trade markers in year							
	2000	2001	2002	2003	2004	2005	2006	Total
Micro	62	101	59	52	71	101	65	511
Small	274	253	277	237	267	284	255	1847
Medium	541	515	515	519	492	516	510	3608
Large	799	839	808	771	755	737	760	5469
Total	1,676	1,708	1,659	1,579	1,585	1,638	1,590	11,435
	Percentage of firms that trade mark in year							
Micro	0.3	0.5	0.3	0.3	0.4	0.5	0.4	0.4
Small	1.8	1.6	1.7	1.4	1.7	1.8	2.2	1.7
Medium	5.5	5.0	5.0	5.0	4.9	5.6	5.8	5.2
Large	13.2	12.9	12.9	12.5	12.3	12.5	14.3	12.9

Notes: These are unweighted totals reflecting numbers of firms in the data for which firm size can be classified in the year, i.e. for which employment is known. Source: Greenhalgh et al. 2011 Table 2.

Table A2 Trade marking firms by technology sector and UK-CTM breakdown

	No trade marks	Trade-markers	UKTM only	CTM only	Both UK and CTM	UKTM/All ratio
High tech	2,739	298	109	84	105	0.366
Medium tech	5,609	433	200	95	138	0.462
Other manufacturing	24,053	1,805	964	292	549	0.534
Non-manufacturing	187,287	4,119	2,506	597	1,016	0.608
Total	219,688	6,655	3,779	1,068	1,808	0.568

Notes: These are unweighted totals reflecting numbers in the data. Source: Greenhalgh et al. 2011 Table 4.

Table A3 Summary statistics for growth regressions

Variable	Description	Mean	Std. Dev.
Growth employ	Growth employment 2003-06	0.0702	0.2467
Log employ 2003	Log employment in 2003	5.2903	1.5257
TM dummy	Trade marker dummy (any 2000-03)	0.1205	0.3256
TM stock	Trade mark stock (15% depreciation)	2.6691	19.191
Log Adv Stock	Log Advertising & Mkting stock (15%)	4.8882	2.4445
Industry TMs int.	Industry TMs/employment (SIC3)	0.0745	0.1310
Industry patent int.	Industry patents/employment (SIC3)	0.0292	0.0943
Exporter	Dummy for exporter (2003)	0.3799	0.4854
Foreign	Dummy for foreign owned (2003)	0.4046	0.4908

Note: For reference, the median value for employment growth is 0.0156. The statistics in this table are for the n=8470 firms for which data existed for 2000-2006. Source: Greenhalgh et al. 2011, Table 22.

Table A4 Regression variables for employment and wages

Variable	Description	Mean	Std. Dev.
Employment	log of no. of employees in the firm	5.539	1.494
Sales	log of firm turnover	9.465	1.884
Industry real wage	log of industry real wage	2.107	0.221
Industry materials costs	log of industry materials prices	6.721	2.627
Real interest rate	Real interest rate	1.032	0.007
TM dummy (t-1)	Trade marker dummy (t-1)	0.111	0.315
TM intensity (t-1)	Trade marks per 100 employees (t-1)	0.171	5.218
Patent dummy (t-1)	Patent dummy (t-1)	0.029	0.169
Patent intensity (t-1)	Patents per 100 employees (t-1)	0.030	0.390
Firm nominal pay	log firm annual earnings/employee	9.956	0.151
Industry nominal wage	log of industry nominal hourly wage	2.279	0.169
Advertising (t-1)	log of advertising (t-1)	3.668	2.559

Source: Greenhalgh et al. 2011, Table 16.

References

Audretsch, D. , L. Klomp, E. Santarelli, and A. Thurik (2004). Gibrat's Law: Are the Services Different? *Review of Industrial Organization* 24: 301-324.

Bloomberg (2006). Special Report – Innovation: The world's most innovative companies. *Businessweek*, April 24, 2006.

Greenhalgh, C., D. Bosworth and M. Longland (2001). Technological activity and employment in a panel of UK firms. *Scottish Journal of Political Economy*, 48(3): 260-282.

Greenhalgh C., and M. Longland (2001). Intellectual property in UK firms: Creating intangible assets and distributing the benefits via wages and jobs. *Oxford Bulletin of Economics and Statistics,* Vol. 63, Special Issue: The Labour Market Consequences of Technical and Structural Change.

Greenhalgh C. and M. Rogers (2010). *Innovation, Intellectual Property and Economic Growth*, Princeton University Press, Chapter 10.

Greenhalgh, C., M. Rogers, P. Schautschick and V. Sena (2011). *Trade Mark Incentives*, a report for the UK Intellectual Property Office, forthcoming.

Harrison, R., J. Jaumendreu, J. Mairesse and B. Peters (2008). Does innovation stimulate employment? A firm-level analysis using comparable micro-data. NBER Working Paper 14216.

Hart, P. and N. Oulton (1996). Growth and size of firms. *Economic Journal* 106: 1242-1252.

Hart, P. E. and N. Oulton (1999). Gibrat, Galton and job generation. *International Journal of the Economics of Business* 6(2): 149-164.

Helmers, C., M. Rogers and P. Schautschick (2011). Firm-level analysis of intellectual property in the UK: The Oxford Firm-level Intellectual Property Database, mimeo University of Oxford.

Koch, C., C. Helmers, and M.Rogers (2010). Firm growth and firm size. *Applied Economic Letters* (iFirst): 1-4.

Lancaster, K.J. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74, 132-57.

Lancaster, K.J. (1971). *Consumer Demand: A New Approach*. Columbia University Press, New York.

Landes, W. M. and R. A. Posner (1987). Trademark law: an economic perspective, *Journal of Law and Economics* 30(2): 265-309.

Lopes, T. and P Duguid (eds.) (2010) *Trademarks, Brands and Competitiveness*, Routledge: New York, N.Y. and Abingdon, Oxon.

Mendonca, S., T. Pereira and M. Godinho (2004). Trademarks as an indicator of innovation and industrial change. *Research Policy* 33: 1385-1404.

M Pianta, (2004). Innovation and employment, Ch.22 of J Fagerberg, D Mowery and R Nelson, (eds.), *The Oxford Handbook of Innovation*, Oxford University Press.

Robjohns, J. (2006). ARD2: the new Annual Respondents Database. *Economic Trends* 630(May): 43-51.

Rogers, M., C. Helmers, and C. Greenhalgh (2007). An analysis of the characteristics of small and medium enterprises that use intellectual property. Report for UK Intellectual Property Office, http://www.ipo.gov.uk/pro-ipresearch.htm

Van Reenen, J. (1996). The creation and capture of rents: wages and innovation in a panel of UK companies. *Quarterly Journal of Economics*, 111(1).

Van Reenen, J, (1997). Employment and technological innovation: evidence from UK manufacturing firms. *Journal of Labor Economics,* 15(2): 255-84.