Trade Mark Incentives

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Executive summary

What is this report about?

The research was commissioned by the UK Intellectual Property Office (IPO) to investigate potential links between trade marking and performance. Specifically, researchers were asked to:

(1) document an overview of corporate trade marking activity in Britain;

(2) analyse the role of trade marks in the innovation process for firms and their impact on households;

(3) explore possible links between trade marking and branding.

Within this document we draw on three views of trade marks:

(a) their unique nature guarantees a product's origin to the customer, so it acts as an information signal;

(b) the registration of a trade mark occurs when a new product is brought to market, so it acts as a signal of innovation;

(c) the registration of the product name signals the start of a process of building a strong new brand for the firm.

Overview of the data

Our starting point is the Office for National Statistics (ONS) Annual Respondent Database (ARD2) for the years 2000-2006. The ARD combines information from ONS business surveys over time, covering all large firms but with a sampling design for smaller firms. To this we have added data on each firm's UK and European Community trade marks and patents drawn from official records.

Our analysis shows that large firms are much more likely to trade mark (12.9%) than smaller firms, with micro firms the least likely (0.4%). Just 1.7% of small and 5.2% of medium sized firms trade mark their products and services. Trade marks are used in every sector of the economy, with manufacturing, wholesale/retail services, and business services the three sectors that use them most.

We calculate the ratio of UK trade marks to all trade marks, including European Union (or 'Community') trade marks, as an indicator of each sector's internationalisation. The most internationalised sector – that with the lowest ratio - is communications (0.439), followed by computer software (0.477) and manufacturing (0.505). The average for all firms was just above half (0.567), reflecting substantial use of the Community trade mark (CTM).

We also classify firms into high - and medium - tech manufacturing groups, along with other and non-manufacturing groups, mainly services. The proportions trade marking are: high-tech firms 9.8%, medium tech firms 7.2%, other manufacturing 7.0% and non-manufacturing 2.2%. However, within this last category there are some highly active sectors in absolute terms and some very international sectors.

Is trade marking associated with higher productivity?

An initial analysis, based on the augmented ARD data, suggests that trade marking firms are 21% more productive than those that do not trade mark. This analysis controls for variables such as workforce size, capital assets, export status and foreign ownership, but not for the extent or nature of innovation, which trade marking may proxy, nor for a wider range of characteristics of the firm that may underlie both its trade mark activity and its productivity performance. For example, when we control for the recent level of advertising expenditure in the firm, the productivity differential for trade marking falls to 7%.

We find that a higher intensity of trade marking (more trade marks per employee) is also associated with better productivity. However more advanced statistical analysis reduces the magnitude of these associations. For example, when we control for a ‘time invariant, firm specific effect’ (which controls for persistent differences between firms) we find that the rate of increase in productivity, as trade mark intensity rises, falls to about 1/6th of its original value.

We also investigate the impact of trade marking on productivity using the Community Innovation Survey (CIS4) data. On this much smaller sample, we can include variables reflecting reported innovation, R&D spending, marketing, management ability and employee human capital. This acts as a further robustness test. As might be expected, the inclusion of direct measures of innovation from the CIS, together with information about the quality of the workforce, removes the statistical significance of the trade marking-performance result (although it is still positive). Further analysis suggests it is only younger and smaller firms that improve their productivity from raising their trade mark intensity.

Do trade mark active firms have higher employment?

We demonstrate that employment is significantly higher in firms that are trade mark active (even when controlling for the size of firms). The strength of the association is such that a firm that regularly trade marks has a workforce that is 20% larger than a similar firm which does not. This suggests that the activity of developing and offering new products and brands to the marketplace requires more employees.

Do trade mark active firms pay higher wages?

When we analyse average wages, we find that trade marking firms pay slightly more on average to their employees – a 0.7% premium. We are unable to determine whether this reflects higher hourly wage rates, longer working weeks or higher levels of skills.

However, the findings for employment and wages taken together suggest that firms that regularly trademark support more ‘good jobs’, with employees who are producing and marketing new products and developing new production techniques.

The benefits for households

In reporting the gains to firms we have suggested that regular trade marking often signals innovation. Much of this innovation is likely to be incremental, although some will involve the introduction of radically new products, adapting new process technology to deliver genuinely new goods and services. Such innovation leads to lower prices, higher quality and a greater variety of products in the marketplace.

Consumers will benefit from all three – lower prices increase their real purchasing power; higher product quality at similar prices to earlier inferior varieties gives the customer more value for money; and the increased variety of goods and services is more likely to satisfy customer needs. All these features of innovation can thus increase consumer satisfaction.

Is trade marking associated with higher growth?

The analysis calculates growth of employment and turnover over the period 2003-2006. We then use trade marking and advertising data from 2000 to 2003 to construct for each firm both a trade mark dummy variable (indicating some activity in this period) and its stock of trade marks and advertising in 2003 (the initial year of the growth period).

The analysis shows that firms that were trade marking from 2000 to 2003 saw their employment and turnover both growing at a rate of 6% per annum faster than other firms during 2003-2006. For both the growth of employment and turnover, the regression analysis controls for firm age, industry levels of trade mark and patent intensity, exporter status and foreign ownership. When we add the stocks of advertising and trade marking to this regression in place of the simple trade mark dummy, the differences in growth and turnover are also significant.

However, when we add a measure of interaction between the stock of each firm's trade marks and its advertising stock to both growth models the coefficient is negative, although not significantly so. What interpretation should we place on this finding? It is contrary to our expectations: we expected that joint trade marking and advertising activity might indicate brand building and, if so, these stocks would be complementary and further strengthen a firm's growth.

Having only four years of data for the calculation of stocks may be too short for such synergies to be uncovered. Furthermore, money spent on trade marks cannot be spent on advertising; hence there is an inherent substitution between these activities. However, there is some good news, as it suggests that trade marks are less likely to support anti-competitive brand building by incumbent firms.

Conclusion

In this report we have investigated the statistical relationship between trade mark activity and the performance of firms in productivity, employment, wages and growth rates. In all these dimensions, our analysis has shown positive correlations between being trade mark active and delivering better performance. In some dimensions, there were further positive correlations between increasing the trade mark intensity of the firm and performance.

We are cautious about assigning direct causality from trade marks to performance, as many of the results were obtained using a pooled dataset of observations both across firms and through time. As the regression data covered only six years, we found that more rigorous panel data methods reduced the strength of the positive relationships. This is likely to be due to less year to year variation in trade mark activity within firms than between firms. We do not know whether data covering a longer time span would restore the size and significance of the correlations.

Nevertheless the positive associations that we have uncovered indicate that trade mark active firms are different in important and valuable ways from other firms. This should reassure policymakers, who design innovation policy to encourage domestic producers to compete on product quality and variety, not just cost and price, and to use trade marks to signal their innovations.

1. Introduction

The research was commissioned by the IPO to investigate any potential link between trade marking and performance. Researchers were asked to:

(1) Report on the type of companies using and applying for trade marks with coverage in the UK, with a view to understanding trade-marking activity in Britain.

(2) Use the linked data to assess the role of trade marks in the innovation process for products, their value to firms, effect on growth and impact on households.

(3) Distinguish between trade marking and branding, in terms of advertising and related firm expenditure, to analyse how the two interact.

The broad structure of this report follows these research aims. In sections 2 and 3 we discuss the data we created and used to document trade mark activity. Section 4 contains our main analysis. We look at a range of performance measures and seek to understand the role of trade marks. There is also a summary of the impact on households. Section 5 takes a closer look at trade marking and branding, something only touched on in section 4. Section 6 provides our conclusions. The remainder of this introduction gives a brief overview of the nature and role of trade marks.

1.1 The nature and role of trade marks

Before proceeding to the statistical analysis, it may be useful to identify how the economic literature views the use of trade marks by firms and to note some of the possible ambiguities surrounding their value to society. Three views of trade marks are discussed in the literature: first, the unique nature of the registered mark gives the customer a guarantee of the origin of the product, acting as an information signal; second, the registration of a trade mark occurs when a new product is brought to market, so acting as a signal of innovation; third, the registration of the product name is the start of a process of building a strong new brand for the firm.

That trade marks offer a guarantee of origin is intrinsic in their legal underpinning: the law protects a firm that has registered its trade or service mark from actions by other firms to copy the name, or imitate it, in ways that might confuse or deceive the consumer. Economists have developed this idea further, arguing that the trade mark offers a guarantee of quality, not just of source. Landes and Posner (1987) posited that trade marks improve market efficiency by signalling the quality of a product to potential customers. Without this signal, consumers would have to expend scarce time and effort searching for evidence of product quality. In their view, trade marks help to solve what economists call the ‘information asymmetry’ between the seller, who knows the quality of a product, and the buyer, who does not, thus enhancing market efficiency.

A slightly different view of the informational value of a trade mark is that it acts as a signal of innovation. While there are other types of intellectual property, such as patents, that suggest invention, these are restricted to highly original elements of product and process design, as a patented item must be novel, not obvious in nature even to experts, and capable of industrial application. In practice many smaller innovations in product design and services fail to meet these requirements, so are not patented. Also, there can be a delay of several years between a patent application and a product going to market: for example, new medicines are subject to extensive testing and regulatory approval. Thus, trade marks, which are used by more economic sectors than patents, can be a useful alternative indicator of innovation. There is evidence of a positive correlation between innovation and trade mark activity across a number of European countries, see Mendonca et al. (2004). Firms need to inform their customers and investors about their innovative activity, so they are likely to apply for trade marks close to their product launch.

The third interpretation of trade marks is that they form a basis for building successful brands. Firms want to have a portfolio of strong quality brands as this ensures customer loyalty and deters new firms from entering the market. To build such a portfolio, firms will register trade marks for their new products and then engage in promotional advertising and other marketing activities, such as short-term price discounting. Over time, they want the brand to embody a lifestyle and acquire significance beyond its distinctive name. When this occurs, it can also make it easier for a firm to apply a trusted trade marked name in new fields of activity, reducing the need for advertising.

So, with the first and second interpretations, we can argue that trade marks are likely to improve the efficiency of markets. However, this is likely to be less so with brand-building, as this activity is essentially anticompetitive and benefits incumbent firms by excluding new competitors who might offer better products at a lower price that would enhance consumer welfare. There is also a conundrum in global markets, where the need for successful domestic brands to engage in worldwide competition in order to retain profits and jobs in the economy has to be balanced against the promotion of new firms within the domestic economy (otherwise such firms might not grow to be successful in export markets).

At various points in the report we shall refer to these theories and enlarge upon them where necessary to interpret our empirical findings correctly.

2. Data

This section describes the different datasets used to construct the integrated database in our analysis. The basic starting point is the Office for National Statistics (ONS) Annual Respondent Database (ARD2) for the years 2000-2006. The ARD is not a population database and has a sampling design for smaller firms.[1] The largest data set we use has 338,663 firm-year observations which represent 226,343 firms. These firms have around 9.2 million employees and represent about 35% of Gross Domestic Product (GDP) in 2005. This data set is augmented by trade mark data from OFLIP, a population database for UK firms registered at Companies House. Further details are in Data Appendix.

The OFLIP database has information on UK trade mark publications and European Union (Community) trade marks registered for each firm in the Fame database of UK and Irish financial company information and business intelligence (see Rogers et al, 2007, for further details). One relevant issue is that while firm-level trade mark data is straightforward for 'standalone' firms, it is more complex when firms have subsidiaries. OFLIP also has aggregate, or consolidated, trade mark data for 'group' firms (based on Fame information on ownership structure). In this study, we use consolidated intellectual property (IP) data when the firm has subsidiaries. Where a firm is labelled a Fame subsidiary, we also use the trade mark total for its group. There are arguments for and against using consolidated data; hence, we also considered the *un*consolidated results for the majority of regression analysis. Overall, we found few qualitative differences, although the significance was generally better using consolidated data.

Our original intention was to use ONS firm-level trade mark data. Delays led us to use OFLIP data instead, though late in the project we undertook a preliminary analysis of the ONS data, dividing it into 'definite' and 'possible' matches to firms applying for trade marks. Since all OFLIP data are based on definite matches, we decided to compare them to the ONS matches. Between 2000 and 2006, there were 27,065 ONS definite matches compared to 73,238 OFLIP definite or possible matches. It may be useful to investigate such large differences further – 'possible' matches in the ONS data are substantial – but time required us to focus on the OFLIP data for now.

The large ARD2 data set of 338,663 firm-year observations cannot be used for our productivity analysis, which requires gross value added and capital stock. The availability of these variables reduces the sample to 35,279 firm-year observations. This sample is dominated by large (55.0%) and medium firms (33.2%). In 2005, total employment for this sample is around 5.7 million and total value added (nominal) around £239 billion (or approximately 20% of GDP).

1 The sampling design of the ARD has changed overtime. For the 2000-2006 period the intention was to sample micro firms (1-9 employees) at 25%, firms with 10-99 employees at 50%, firms with 100-249 employees at 100% or <50% depending on industry, and all larger firms (250 plus). See Robjohns (2006)

3. Understanding the trade mark data

This section presents some summary statistics for the ARD2-OFLIP data, providing background for the analysis to follow. We analyse the data for 2000-2006.

Table 1 Firm size in our ARD2 dataset, by year shows the numbers of companies each year in our dataset, by size of firm. The table covers 226,343 firms with 338,663 firm-year observations. Firm size is defined by employment. A micro firm has 1–9 employees, a small firm has 10–49, medium has 50 –249, and a large firm has more than 250 employees. This means all firms must have employment data. The numbers of observations falls in 2006 by around 19% as the ARD2 coverage falls that year. The total employment of the 47,863 firms in the sample in 2005 is 9.1 million (producing 35% of GDP).

Table 1 Firm size in our ARD2 dataset, by year

Year	2000	2001	2002	2003	2004	2005	2006	Total
Micro	19,554	22,254	19,042	18,442	18,705	18,689	14,895	131,581
Small	15,199	15,310	15,956	16,149	15,886	15,262	11,246	105,008
Medium	9,219	9,728	9,868	9,829	9,539	8,757	8,235	65,175
Large	5,277	5,642	5,474	5,411	5,379	5,155	4,561	36,899
Total	49,249	52,934	50,340	49,831	49,509	47,863	38,937	338,663

Of the 49,249 firms observed in 2000, 1,676 of these firms had a UK or Community trade mark in that year. The numbers and propensity of trade marking by company size and year are shown in Table 2. The table shows that the absolute number of trade marking firms has been remarkably stable over the period.

The percentage of firms that trade mark each year is shown in the second panel. There are large differences in the propensity of different sized firms to trade mark. Although the table uses unweighted data, within the different company size groups the percentage of firms using trade marks is roughly accurate.2 Large firms are clearly much more likely to trade mark (12.9%); even so, 5.2% of medium sized firms are trade mark active. By contrast, only 1.7% of small firms trade mark and few micro firms (0.4%) do so.[3]

2 This is because the main stratification for the ARD is by firm size.

3 Nevertheless, as shown in Rogers et al. (2007), because of the very much larger numbers of smaller firms in the economy, the total number of trademarks taken out by SME and micro firms exceeded the total for large firms for each year in this period.

Table 2 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	11435
	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 in data.

Table 3 below gives a sectoral breakdown of the numbers of trade marking firms for 2000-2006. The three sectors most likely to trade mark are manufacturing, wholesale/ retail, and business services. The table also provides a breakdown of firms that only took out UK trade marks, those that only took out European Community marks, and those that took both. The ratio of 'UK to all' is also shown. The lowest ratios (indicating the most use of international marks) are in the communications, computer and manufacturing sectors.

Table 3 Trade marking firms by sector, and UK-CTM breakdown

	No Trade marks	Trade-markers	UKTM Only	CTM Only	both	UKTM/All ratio	Total
Manufacturing	31,920	2,481	1,252	458	771	0.505	34,401
Construction	21,559	141	102	14	25	0.723	21,700
Wholesale, retail	64,794	1,584	951	230	403	0.600	66,378
Hotel, restaurants	12,844	153	96	14	43	0.627	12,997
Transport	9,304	221	133	29	59	0.602	9,525
Communications	1,180	66	29	14	23	0.439	1,246
Real estate	7,382	100	70	12	18	0.700	7,482
Computer related	7,087	277	132	77	68	0.477	7,364
Business services	31,391	848	502	137	209	0.592	32,239
	28,362	560	380	56	124	0.679	28,922
Total	215,823	6,431	3,647	1,041	1,743	0.567	222,254

Notes: The observations in this table do not sum to 226,343 since ONS confidentiality rules have meant some sectors have been deleted (agriculture, mining, EGW, and finance). These are *unweighted* totals reflecting numbers in data. Full details of trade marking in these sectors for 2000-2005 can be found in Rogers et al, 2007.

Table 5 groups firms into high- and medium technology, other manufacturing and non-manufacturing (again for 2000-2006). Although not shown directly, the proportion of high-tech firms trade marking is 9.8%, followed by medium tech (7.2%), other manufacturing (7.0%) and non-manufacturing (2.2%). Similarly, the ratio of 'UK to all trade marks' is lowest for high-tech and highest for non-manufacturing firms, indicating that this last sector is dominated by smaller firms that rely more on local markets.

Table 4 Trade marking firms by technology sector, and UK-CTM breakdown

	No Trade marks	Trade-markers	UKTM Only	CTM only	both	UKTM/All ratio	Total
High tech	2,739	298	109	84	105	0.366	3,037
Medium tech	5,609	433	200	95	138	0.462	6,042
Other manufacturing	24,053	1,805	964	292	549	0.534	25,858
Non-manufacturing	187,287	4,119	2,506	597	1,016	0.608	191,406
Total	219,688	6,655	3,779	1,068	1,808	0.568	226,343

Notes: These are *unweighted* totals reflecting numbers in data

Table 5 shows the age of firms still operating in 2005, and their trade mark activity. As can be seen, the oldest firms (31 years and over) account for most trade marking firms, but the numbers of trade markers increases once firms have passed their tenth anniversary. Firms aged 31+ are most likely to trade mark (13.0%) followed by the 16-20 age (11.6%). The newest firms are least likely to trade mark (1.7%) and have the highest ratio of 'UK to all'.

Table 5 Firm age (2005) and trade marking

Firm Age	No Trade marks	Trade-markers	UKTM only	CTM only	both	UKTM/All ratio	Total
1-5	9,267	159	101	39	19	0.635	9,426
6-10	7,190	322	198	56	68	0.615	7,512
11-15	8,430	665	383	101	181	0.576	9,095
16-20	5,458	715	364	102	249	0.509	6,173
21-25	3,703	438	226	61	151	0.516	4,141
26-30	2,997	294	148	31	115	0.503	3,291
31+	7,153	1,072	511	141	420	0.477	8,225
Total	44,198	3,665	1,931	531	1,203	0.527	47,863

Notes: These are *unweighted* totals reflecting numbers in data

Most firms in the data are in the South East, including London. Table 6 shows that 2,677 South East firms (3.5%) have trade marks, the highest propensity of any region and is likely to reflect the size and age issues discussed above. Around 3% of firms in East Anglia, West Midlands, East Midlands, Yorkshire & Humberside trade mark.[4]

Table 6 Regions and trade marking

	No Trade marks	Trade-markers	UKTM only	CTM only	both	UKTM/All Ratio	Total
South East	74,551	2,677	1,361	498	818	0.508	77,228
East Anglia	8,749	263	145	54	64	0.551	9,012
South West	19,396	451	286	63	102	0.634	19,847
West Midlands	18,481	589	345	88	156	0.586	19,070
East Midlands	15,427	489	286	71	132	0.585	15,916
Yorkshire & Humber	17,172	544	328	67	149	0.603	17,716
North West	19,851	684	419	99	166	0.613	20,535
North	8,072	196	120	31	45	0.612	8,268
Wales	10,494	273	179	34	60	0.656	10,767
Scotland	27,495	489	310	63	116	0.634	27,984
Total	219,688	6,655	3,779	1,068	1,808	0.568	226,343

4 To the extent that firm size composition differs across regions, these unweighted figures will provide only a rough guide to regional differences.

4. Role of trade marks in innovation

This section explores how trade marking impacts more widely on firms and households. We start from the hypothesis that trade marking is a proxy for innovative effort such as the launch of a new or improved product.

When firms introduce innovations into their products, they hope to benefit from increased market share, higher profitability and greater customer loyalty. Process innovation affects the way a product is produced and generally lowers its cost. Product innovation refers to the phenomenon of commercialisation of novel products, or better varieties of existing products, embodying a wider range of characteristics. The firm's customers benefit from lower prices or improved quality, or both.

If we accept that trade marks are typically applied for just before new or improved varieties of goods and services are introduced to market, then we can assess the value of innovation to firms by estimating the relationship of new trade mark applications to a firm's level of real net output, or value added. Potential productivity gains may come from two routes: where the firm has achieved a process innovation it makes savings in input resources; when the firm offers a new or better product it can charge a higher unit price despite using similar inputs.[5]

Thus, with either product or process innovation we would expect to observe a rise in value added per unit of input, which measures total factor productivity. Earlier studies using UK data have shown this positive relationship: Greenhalgh and Longland (2005) demonstrated this for a panel of large manufacturing firms observed from 1988-94, while Greenhalgh and Rogers (2010b) analysed 1600 large manufacturing and services firms for 1996-2000 and also found a positive association between trade marks and productivity. In this project we analyse firms of all sizes and sectors using more recent data.

The following section begins our analysis of how trade marking is associated with the performance of the firm, focusing on productivity, both relative levels and changes over time. In later sections we look at employment and labour demand.

5 Note that the firm's higher price is not 'deflated out' of the measure of real output when an average price index for all firms is used to deflate nominal values of sales.

4.1 Trade marking and productivity

Our main interest is in explaining gross value added (GVA) at the level of the firm. This is a variable in the ARD2 dataset and is defined in market prices. As is standard, we use deflators to convert GVA (at market prices) into real terms.[6] Using *Y* to represent this 'real' GVA we can write

$$Y = AL^{\alpha_1}K^{\alpha_2}R^{\alpha_3} \qquad [1]$$

where *L* is labour, *K* is tangible capital, *R* represents intangible capital built up by the firm and *A* is a parameter representing the impact of external knowledge to the firm.[7] Various studies focus on different components of intangible capital including intellectual property (IP), ICT, training, advertising, marketing, organisational skills and management techniques. A standard interpretation is that raising *R* allows the firm to generate more real sales and hence higher value added. However, it is also possible that there is a market power or 'price' interpretation (e.g. raising *R* allows the firm to generate more nominal sales *since prices can be raised* and hence value added is increased).[8]

Taking logs, *i*=firms, *t*=year, *j*=industry, u_i = firm specific effect, e_{it} = error

$$y_{it} = \beta_t + a_j + \alpha_1 l_{it} + \alpha_2 k_{it} + \alpha_3 r_{it} + u_i + \varepsilon_{it} \qquad [2]$$

Since we cannot measure *r* directly, at least using the ARD data, we use annually published trade mark and patent data as a proxy for intangible capital. We begin by setting a value of 1 (a 'dummy variable') if a trade mark (or patent) application was made. We also calculate the intensities of trade mark and patent activity relative to firm size. To allow some control for the possibility that high productivity firms may generate more IP, we lag these variables by one year. The ARD data also has a variable for advertising and marketing services (in £000s) which we use as another proxy for intangible capital.

6 Variables are deflated at the 4-digit SIC level where possible. Lower digit level deflators are used where possible. Prices indices for gross output, intermediate goods and value added were taken from the EU KLEMS data base and expanded where incomplete. This was done using the producer price indices for SIC 14-40 and the service producer price index provided by the ONS. For details on EU KLEMS see http://www.euklems.net/. The base year is 1995.

7 The presence of A in [1] requires some explanation. In economic growth theory, A represents the level of knowledge or technology available to the firm, which would include any contribution from in-house R&D. However, in the empirical R&D productivity literature some authors leave in the A term (e.g. Hall and Mairesse, 1995, although they do not define it), while others omit it entirely (e.g. Bond et al, 2002). Leaving A in [1] makes it clear that there can be external, knowledge-based, effects on productivity, due to spillovers.

8 In theory, the deflators used might remove this 'price' effect. However, we do not have data on firm-level price deflators – a situation that is common to almost all productivity analyses.

Table 7 Regression variables

Variable	Description	Mean	Std. Dev.
log K	log of capital stock	9.134	2.079
log L	log of employees (pit)	5.533	1.501
TM dummy	Trade marker dummy (t-1)	0.110	0.313
TM intensity	Trade marks per 100 employees (t-1)	0.169	5.000
Patent dummy	Patent dummy (t-1)	0.029	0.169
Patent intensity	Patents per 100 employees (t-1)	0.029	0.387
Industry TMs int.	Industry TMs/ employment (SIC3)	0.083	0.139
Industry patent int.	Industry patents/ employment (SIC3)	0.031	0.085
log Advertising	log of advertising (t-1)	3.671	2.565
TM dummy * log Adv	Interaction	0.672	2.069
Exporter	Dummy for exporter	0.148	0.355
Foreign	Dummy for foreign owned	0.446	0.497
Own unknown	Dummy for own. uncertain	0.101	0.302

Notes: Industry TMs and patent intensities are defined using sum of IP where j≠i.

4.1.1. Pooled OLS using dummies for trade marking

Table 8 below shows pooled, OLS regression for all the observations in our sample. Sector and year dummies are also included; though highly significant, their coefficients are not shown. This type of regression is often considered unreliable since: a) there are likely to be many unobserved aspects to firms that we do not control for (the u_i), and b) the explanatory variables may themselves be explained by the value added (termed 'endogeneity'). In both cases, these factors may cause some bias in coefficients. Nevertheless, the results provide some basic evidence on conditional associations in the data.[9]

The first column includes only the logs of labour and capital, with year and sector dummies (which are significant as groups in all regressions at 1% level with F-test). The coefficients indicate constant returns to scale. The second column adds a trade mark dummy and various other variables. The lagged trade mark dummy has a coefficient of 0.21, which implies that trade mark activity is associated with a 21% higher level of value added. Since we control for capital and labour in the regression, we can also consider this a 21% difference in total factor productivity.[10] While this association does control for a variety of variables, we discuss below how trade marks might act as a proxy for other (unobserved) factors.[11]

Regression [3] includes the lag of the log of advertising. This has a significant positive association with value added (a 10% increase in advertising is associated with a 1% increase in productivity). As might be expected, its inclusion reduces the magnitude of the coefficient on the trade mark dummy (now indicating a 7% productivity premium). Regression [4] includes an interaction term – the lagged trade mark dummy x the lag of the log of advertising – which has a significant and negative coefficient. The implication is that trade marking and advertising are *substitutes*. It should also be noted that the coefficient magnitude for the trade mark dummy has risen to 0.43. If we consider a firm

9 We should be clear on this issue: our analysis should be viewed as a descriptive regression that yields conditional associations. Econometrically, using OLS will give us the BLP (best linear predictor) of value added given the explanatory variables. However, without further assumptions concerning how firms behave (including how they invest), we cannot claim the coefficients are estimates of an underlying model of firm behaviour. As can be imagined, specifying an accurate model of firm behaviour in order to estimate production functions has attracted many contributions and remains contentious (see Griliches and Mairese, 1995, Pakes and Olley, 1996, Levinsohn and Petrin, 2003, Bond and Soderbom, 2005; a recent review and investigation with UK data is in Eberhardt and Helmers, 2010). These issues are one part of so-called structural estimation; see Reiss and Wolak (2007).

10 We did investigate using Community trademarks and UK trademarks separately in the analysis. However, especially when it came to using intensities (see next section) we found that the statistical estimates could not distinguish between the two types of trademarks.

11 Note even when using the pooled OLS estimator, the (lagged) patent dummy coefficient is not significant. We also include variables for the industry trademark and patent intensity at the 3-digit level (i.e. trademarks / employment) as basic indicators of potential spillovers from other firms. In regression [2] the industry trademark intensity is significant, but in regressions [3] and [4] this significance disappears.

with mean advertising (log Advertising =3.7), then the implied magnitude on trade mark dummy is 0.43 – (3.7 x – 0.06) = 0.21. Hence firms with advertising less than the mean have a trade mark-productivity association above this. We view these results as thought provoking, but very preliminary, partly due to the limitations of OLS, but also since trade marking is represented by a single dummy variable.

The inclusion of advertising also slightly reduces the coefficient on the exporter dummy (from 0.33 to 0.30), nevertheless these simple OLS estimates indicate that exporters are associated with much higher productivity. As with the interpretation of the trade mark dummy, this association does not necessarily mean that exporting raises productivity; it could also be that high productivity firms are engaged in exporting.

Table 8 Pooled OLS regressions with trade mark dummy

	(1)	(2)	(3)	(4)
Log K	0.2815*** (0.0164)	0.2634*** (0.0165)	0.2270*** (0.0162)	0.2271*** (0.0162)
Log L	0.7417*** (0.0219)	0.7398*** (0.0219)	0.6869*** (0.0208)	0.6891*** (0.0208)
TM dummy (t-1)		0.2126*** (0.0221)	0.0671*** (0.0218)	0.4311*** (0.0582)
Patent dummy (t-1)		0.0375 (0.0500)	-0.0088 (0.0499)	-0.0059 (0.0503)
Industry TMs int. (t-1)		0.2173*** (0.0647)	-0.0632 (0.0598)	-0.0657 (0.0596)
Industry patent int. (t-1)		-0.1804 (0.1705)	-0.1392 (0.1635)	-0.1655 (0.1632)
Exporter		0.3329*** (0.0270)	0.2960*** (0.0262)	0.2959*** (0.0262)
Foreign owned		-0.0402* (0.0224)	-0.0262 (0.0218)	-0.0214 (0.0217)
Ownership unknown		-0.1771*** (0.0359)	-0.1485*** (0.0345)	-0.1465*** (0.0344)
log Advertising (t-1)			0.1127*** (0.0056)	0.1192*** (0.0059)
TM dummy (t-1) x log Adv. (t-1)				-0.0626*** (0.0103)
Constant	2.0749*** (0.1679)	2.2343*** (0.1611)	2.6179*** (0.1507)	2.5958*** (0.1516)
Observations	35279	35279	35279	35279
R-squared	0.66	0.66	0.68	0.68

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sector and year dummies also included (both statistically significant as a group at the 1% level).

4.1.2. Trade mark intensity regressions

A second proxy for *r* in equation [2] is the firm's trade mark intensity (defined as (trade marks/employees)*100, or trade marks per 100 employees). This specification now investigates whether doing *more* trade marking (relative to the size of the firm) has any association with value added. Again, since we are using a pooled OLS estimator, there are caveats in interpreting any results. The trade mark intensity is again lagged one year. As shown in Table 7, the mean value for trade mark intensity is 0.17 with a standard deviation of 5.00.[12] The results of the regressions are shown in Table 9. TM intensity has positive coefficient of 0.0046 initially, but falls to 0.0032 when the trade mark dummy and advertising are also included (regression 3).[13] A coefficient of 0.0032 implies that a 1 standard deviation (sd) increase in trade mark intensity is associated with a 0.0032*5 = 0.0160 (or 1.6%) increase in value added (however we note that 1sd is a very high value). Note also that patent intensity is significantly associated with value added: a 1 standard deviation increase is associated with a 0.0501*0.39= 0.0195 (or almost 2.0%) increase.

12 By way of comparison, 'patent intensity' which is defined in the same was as trademark intensity, has a mean of 0.029 and a standard deviation of 0.39.

13 We also investigated non-linear specifications by adding a quadratic TM intensity term but found no evidence for non-linear effects.

Table 9 Pooled OLS regressions with trade mark intensity

	(1)	(2)	(3)	(4)	(5)
Log k	0.2664*** (0.0165)	0.2272*** (0.0162)	0.2271*** (0.0162)	0.2271*** (0.0162)	0.2271*** (0.0162)
Log L	0.7489*** (0.0218)	0.6890*** (0.0207)	0.6880*** (0.0208)	0.6901*** (0.0208)	0.6901*** (0.0208)
TM intensity (t-1)	0.0046** (0.0018)	0.0036*** (0.0013)	0.0032*** (0.0012)	0.0029*** (0.0011)	0.0020 (0.0034)
patent intensity (t-1)	0.0536*** (0.0153)	0.0417*** (0.0146)	0.0501*** (0.0159)	0.0453*** (0.0161)	0.0454*** (0.0160)
Industry TMs int.(t-1)	0.2653*** (0.0685)	-0.0540 (0.0592)	-0.0652 (0.0599)	-0.0675 (0.0597)	-0.0676 (0.0597)
Industry patent int.(t-1)	-0.1835 (0.1696)	-0.1503 (0.1621)	-0.1407 (0.1631)	-0.1662 (0.1629)	-0.1661 (0.1629)
Exporter	0.3379*** (0.0271)	0.2953*** (0.0262)	0.2954*** (0.0262)	0.2953*** (0.0262)	0.2953*** (0.0262)
Foreign owned	-0.0492** (0.0224)	-0.0284 (0.0217)	-0.0261 (0.0218)	-0.0214 (0.0217)	-0.0214 (0.0217)
Ownership unknown	-0.1944*** (0.0360)	-0.1529*** (0.0345)	-0.1488*** (0.0345)	-0.1468*** (0.0344)	-0.1468*** (0.0344)
log Advertising (t-1)		0.1142*** (0.0055)	0.1127*** (0.0056)	0.1191*** (0.0059)	0.1191*** (0.0059)
TM dummy (t-1)			0.0612*** (0.0220)	0.4169*** (0.0583)	0.4181*** (0.0586)
patent dummy (t-1)			-0.0592 (0.0532)	-0.0516 (0.0537)	-0.0516 (0.0537)
TM dummy (t-1) x log Adv. (t-1)				-0.0611*** (0.0103)	-0.0613*** (0.0103)
TM intensity (t-1)x log Adv. (t-1)					0.0002 (0.0006)
Constant	2.1817*** (0.1609)	2.6081*** (0.1502)	2.6127*** (0.1508)	2.5916*** (0.1516)	2.5915*** (0.1516)
Observations	35279	35279	35279	35279	35279
R-squared	0.66	0.68	0.68	0.68	0.68

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Sector and year dummies also included (both statistically significant as a group at the 1% level).

Regressions 4 and 5 also include interactions between trade marking and advertising. Regression 4 again indicates a negative interaction effect for the trade mark dummy and the advertising variable. Regression 5 also interacts advertising with trade mark intensity, but the coefficient is not significant. Further the coefficient on trade mark intensity is now insignificant, indicating that the inclusion of all of these variables has led to high levels of correlation between them.

4.1.3. Fixed effects model

The fixed effect model is derived by subtracting the 'within means' from both sides of [2]. This means that the u_i's are removed from the equation.[14]

$$y_{it} - \overline{y} = (\beta_t - \overline{\beta}) + \alpha_1(l_{it} - \overline{l}) + \alpha_2(k_{it} - \overline{k}) + \alpha_3(r_{it} - \overline{r}) + (\varepsilon_{it} - \overline{\varepsilon})$$

The advantage of this model is that it removes the u_i (the 'firm-specific effect', or time invariantfirm-level impact on value added). Again, since we do not have data for *r*, we use trade mark data as a proxy. This is a 'stronger' test of whether trade marks can be used as a proxy, since the coefficient is estimated on the basis of changes within firms. In other words, we are assessing the association between deviations of a firm's value added from its mean ($y_{it} - \overline{y}$) and deviations of trade marking intensity from its mean $(tm_{it} - t\overline{m})$. The drawback of such a method is that, to the extent that trade marking is *persistent* in a firm, the removal of the firm-specific effect reduces the possibility of finding a role for trade marking.

As Table 10 (regression 1) shows the coefficients for labour and capital have been substantially reduced. This is a common result in FE regressions and is sometimes viewed as a result of the increased 'measurement error' created by the within firm deviations.[15] Regression 2 also includes firm-level trade mark and patent intensity, as well as industry level trade marking and patenting intensity. The only significant coefficient is on trade mark intensity. The magnitude (0.0006) is around one sixth of the size in the OLS regressions. Regressions 3 and 4 include advertising, and the interaction between trade mark intensity and advertising. The coefficient on log of advertising is significant (at 10% level), but the magnitude of this coefficient has fallen (from 0.11 in OLS to 0.0074 here). Based on changes within the firm, therefore, the implication is that a 10% rise in advertising is associated with a very small (0.074%) rise in productivity. Regression 4 also contains a positive coefficient on the interaction between trade mark intensity and advertising (0.0006), while the coefficient on trade mark intensity is now negative (-0.0022). This suggests that firms must advertise to gain benefits from trade marks.

14 There is also the so-called random effects model, which assumes that the ui's are random and uncorrelated with any of the explanatory variables. Further, we can test for whether this assumption appears valid (using a Hausman test). We did this and were able to reject the assumption that the ui's are random at the 1% level.

15 See Griliches and Mairesse (1995, p.11-12), although the issue is, in fact, more complex than 'measurement error'. If, for example, the measurement error for a firm's capital was constant over time, then the within deviation would improve the situation. In practice, as Griliches and Mairesse argue, the nature of the measurement error, as well as uncertainties over lag structures, seem to combine to reduce magnitudes of the coefficients.

Table 10 Fixed effect model

	(1)	(2)	(3)	(4)
Log k	0.1919*** (0.0467)	0.1921*** (0.0467)	0.1903*** (0.0467)	0.1903*** (0.0467)
Log L	0.2419*** (0.0334)	0.2422*** (0.0334)	0.2373*** (0.0335)	0.2376*** (0.0335)
TM intensity (t-1)		0.0006* (0.0004)	0.0006* (0.0003)	-0.0022* (0.0012)
Patent intensity (t-1)		-0.0140 (0.0142)	-0.0150 (0.0143)	-0.0149 (0.0143)
Industry TMs int.(t-1)		-0.0159 (0.0321)	-0.0269 (0.0329)	-0.0270 (0.0329)
Industry patent int.(t-1)		0.0009 (0.1318)	-0.0192 (0.1338)	-0.0185 (0.1338)
log Advertising (t-1)			0.0074* (0.0044)	0.0073* (0.0044)
TM int.(t-1) x log Adv(t-1)				0.0006* (0.0003)
Constant	5.3965*** (0.4600)	5.3940*** (0.4603)	5.4160*** (0.4609)	5.4151*** (0.4609)
Observations	35279	35279	35279	35279
Number of gid	7149	7149	7149	7149
R-squared	0.04	0.04	0.04	0.04

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Year dummies included and are statistically significant as a group at the 1% level.

4.1.4. Dynamic productivity models

Another common approach to estimating productivity is to use a model where current value added (y_t) depends on its past value (y_{t-1}) along with labour, capital and the other explanatory variables listed above, including fixed effects. These models require different econometric techniques (since, for example, adding y_{t-1} to the fixed effect model creates bias if estimated using standard techniques). Further, the alternative techniques allow the possibility of controlling for issues related to the explanatory variables, such as endogeneity. The original estimator is that of Arrellano and Bond (1991) but there are a range of subsequent developments (see Baltagi, 2005).

We tried various estimators based on the Arrellano and Bond (1991) framework and, for each of these, various specifications for lag terms, endogenous variables and instrumental variables. However, it was difficult to get any consistent results. In many cases the specification tests for the validity of the models failed and, when these passed, coefficient magnitudes varied substantially. In general, we found positive coefficients on the trade mark variables, but these were often not significant.

4.1.5 Adding CIS4 data

As discussed above, one of the benefits of trade mark data is that it can act as a proxy for company characteristics such as innovation, R&D, marketing, management ability and employee human capital. However, for this project we also have access to the Community Innovation Survey (CIS4), which has a much wider set of variables allowing us to control for some of these additional factors. CIS defines innovation very broadly, however. Its questionnaire states:

"*A product innovation is the market introduction of a new good or service or a significantly improved good or service with respect to its capabilities, such as quality, user friendliness, software or subsystems. The innovation must be new to your enterprise, but it does not need to be new to your market. It does not matter if the innovation was originally developed by your enterprise or by other enterprises*."

These last two sentences allow the firm to report the introduction in its activities of new products and processes adopted from elsewhere. Economists would generally describe this as the diffusion of new technology rather than as innovation. Nevertheless, it may be useful to compare the CIS and OFLIP data given the access the former has to these wider variables.

Our first set of statistics considers the association between OFLIP trade marking and the CIS4 survey responses on innovation. Table 11 shows data on 16,112 firms surveyed in CIS4. The CIS reports 10,490 (65.1%) of these to be non-innovators during 2002-2004. Of the innovators, 6.4% are process only innovators, 14.9% are product only innovators and 13.6% report doing both. The columns show how many of these firms trade marked at some point between 2002 and 2004 (according to OFLIP data).

We can see that a significant minority of non-innovators *do* engage in trade marking (1,095 of 10,490, or 10.4%). This suggests that a) the CIS survey response fails to report some innovation, perhaps because of time differences, or b) some trade marking does not represent innovation.[16] For 'process innovators' the proportion of trade markers is higher (at 17.7%). The highest share is for 'product and process innovators' where the proportion of trade markers is higher at 29.8%. If we just consider 'product innovators' we can see that 76.4% of such firms *did not* trade mark. This may be because the trade marked products are considered trivial, perhaps associated with the new marketing of an existing product, or the adoption of designs and technology from elsewhere. Alternatively, the firm may have decided that obtaining a trade mark was not worthwhile.[17] Looked at another way, if we assume that all product innovators should trade mark, there is substantial potential for increases in trade mark activity.

16 Of interest for the chances of a) is the fact that of the 691 OFLIP patentees (2002-2004) there are 208 that CIS4 classifies as non-innovators.

17 Many advisers and lawyers would suggest getting a registered trademark for a new product; however, there is legal protection for unregistered trademarks and against 'passing off'. As an example of legal advice "it remains the case that traders are well advised to obtain full registration of all their trademarks, since it will generally make legal disputes over trademarks and brand names simpler and cheaper to resolve" (Jacob et al., 2004, p.78)

Table 11 CIS innovation and trade marking 2002-2004

CIS Innovation Status	OFLIP Trade mark Status Non-trade marker	Trade marker	Total
No Innovation	9,395	1,095	10,490
%	89.6	10.4	100
Process Innovation Only	854	183	1,037
%	82.4	17.6	100
Product Innovation Only	1,832	567	2,399
%	76.4	23.6	100
Process AND Product	1,534	652	2,186
%	70.2	29.8	100
Total	13,615	2,497	16,112
%	84.5	15.5	100

Note: Chi^2 test for null hypothesis of no association returns 672 (prob 0.000).

An indicator of innovation used particularly in studies of manufacturing is R&D expenditure. Table 12 looks at whether R&D and trade marking are associated in this database, which includes firms in all sectors. The CIS4 survey reports that 6,565 firms (40.7% of CIS survey firms) have no R&D expenditure. Of these, 662 (10.1%) also have some trade mark activity in 2002-2004. By contrast, the percentage for R&D active firms is 19.2%.

Table 12 R&D activity and trade marking 2002-2004

	OFLIP Trade mark Status		
Any R&D activity (CIS4)	Non-trade marker	Trade marker	Total
No R&D activity	5,903	662	6,565
%	89.9	10.1	100
R&D active	7,712	1,835	9,547
%	80.8	19.2	100
Total	13,615	2,497	16,112
%	84.5	15.5	100

Note: Chi^2 test for null hypothesis of no association returns 248 (prob 0.000).

4.1.6. CIS regression analysis

There are 2645 firms in the CIS regression sample (i.e. the overlap between CIS4 and our ARD2 2000-2006 regression sample) which allows us to use additional explanatory variables (as set out in Table 13). Again our dependent variable is the log of value added.

Table 13 Regression variables for CIS4-ARD2 sample

Variable	Description	Mean	Std. Dev.
Log Y	Log of value added	9.147	1.710
log K	log of capital stock	9.463	2.107
log L_science	log of employees with science degree	1.516	1.836
log L	log of employees	5.850	1.353
TM dummy	Trade marker dummy (t-1)	0.189	0.392
TM intensity	Trade marks per 100 employees	0.169	5.000
Patent dummy	Patent dummy (t-1)	0.057	0.232
Patent intensity	Patents per 100 employees	0.029	0.387
Industry TMs int.	Industry TMs/employment (SIC3)	0.064	0.109
Industry patent int.	Industry patents/employment (SIC3)	0.032	0.081
Exporter	Dummy for exporter	0.160	0.367
Foreign	Dummy for foreign owned	0.378	0.485
R&D/emp	R&D / employees	0.236	0.600
MachIT/emp	Mach. & IT spend / employees	0.335	0.679
Ext know/emp	Acquisition of external know / employ	0.043	0.223
Train/emp	Training / employees	0.082	0.223
Design/emp	Design spending / employees	0.064	0.280
Market/emp	Marketing / employees	0.137	0.457
Change *	Major change in business structure *	0.522	0.500

Notes: * This variable is based on q.23 of CIS4 which asks ‘Did your enterprise make major changes in the following areas of business structure and practices during the three-year period 2002-2004?’ There are four possible types of change and this variable has the value ‘1’ if any occurred over 2002-2004.

The first regression [1] in Table 14 focuses on capital and labour, along with sector dummies (these are not shown but are always highly significant as a group). Since the CIS survey asks about the proportion of employees with a science degree, we split labour between 'science graduates' and 'other'. The coefficients are all highly significant.[18]

The next regression [2] uses a specification similar to the ones above for the ARD2 regressions, except that we control for whether the firm was a product innovator, a process innovator or both a 'product and process' innovator. Perhaps surprisingly, the coefficient on the 'product innovator only' dummy is not significant (14% level), although it is still positive. The 'process innovator' or 'both product and process' coefficients are positive and significant. The coefficient for the trade mark control or dummy is positive, but not significant (24% level). However, the patent dummy is significant. Regression [3] includes an interaction between 'innovator' – defined as any product or process – and the IP dummies. The 'Innovator*TM dummy' coefficient is negative and significant, while the 'Innovator*patent dummy' is positive and significant. The final regression includes some additional control variables. R&D intensity and marketing intensity have strong positive associations with value added, but the results for trade mark dummy are little changed. Our interpretation is that the presence of the innovator dummies masks the 'trade marker effect' found above.

Table 14 CIS4 regression analysis OLS (IP dummies)

	(1)	(2)	(3)	(4)
log K	0.346*** (0.07)	0.329*** (0.07)	0.329*** (0.07)	0.325*** (0.07)
log L_science	0.111*** (0.03)	0.092*** (0.03)	0.091*** (0.03)	0.081*** (0.02)
log L	0.511*** (0.06)	0.531*** (0.06)	0.531*** (0.06)	0.541*** (0.06)
TM dummy		0.083 (0.07)	0.162 (0.10)	0.160 (0.10)
Patent dummy		0.051* (0.03)	-0.100 (0.08)	-0.126 (0.09)
Product innovator		0.100 (0.06)	0.116 (0.07)	0.108 (0.08)

18 The coefficients sum to 0.97, indicating slightly decreasing returns to scale. One should not take the lower coefficient on 'science graduates' to indicate a graduate is 'worth less', since the average numbers of science graduates working at firms is much less.

Process innovator		0.095*** (0.03)	0.111*** (0.03)	0.064* (0.03)
Both product & process		0.157** (0.06)	0.172** (0.07)	0.011 (0.07)
Industry TMs int.		0.338*** (0.11)	0.337*** (0.11)	0.337*** (0.11)
Industry patent int.		0.605*** (0.16)	0.587*** (0.16)	0.587*** (0.16)
Exporter		0.335*** (0.11)	0.334*** (0.11)	0.334*** (0.11)
Foreign		-0.020 (0.07)	-0.023 (0.07)	-0.023 (0.07)
Innovator * TM dummy			-0.139* (0.07)	-0.183*** (0.06)
Innov * patent dummy			0.218** (0.10)	0.207* (0.12)
R&D/emp				0.144*** (0.02)
MachIT/emp				-0.013 (0.03)
External know/emp				0.017 (0.05)
Train/emp				0.059 (0.15)
Design/emp				-0.077 (0.07)
Market/emp				0.182*** (0.03)
Change				-0.007 (0.21)
Constant	2.934*** (0.436)	2.834*** (0.44)	2.83*** (0.44)	2.83*** (0.42)
Observations	2645	2645	2645	2634
R-squared	0.63	0.63	0.64	0.64

Notes: Dependent variable = log of value added. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sector dummies also included (statistically significant as a group at the 1% level).

Table 15 CIS4 regression analysis OLS (IP intensity)

	(1)	(2)	(3)
log k	0.331*** (0.07)	0.330*** (0.07)	0.325*** (0.07)
log l_science	0.092*** (0.03)	0.091*** (0.03)	0.082*** (0.02)
log l	0.531*** (0.07)	0.532*** (0.07)	0.545*** (0.07)
TM intensity	-0.001 (0.00)	0.060* (0.03)	0.057** (0.03)
Patent intensity	0.082* (0.04)	0.063 (0.07)	0.025 (0.11)
Product innovator	0.101 (0.06)	0.106* (0.06)	0.092 (0.07)
Process innovator	0.098*** (0.03)	0.103*** (0.03)	0.050* (0.03)
Both product & process	0.162** (0.07)	0.167** (0.06)	0.097 (0.06)
Industry TMs int.	0.362*** (0.12)	0.353*** (0.12)	0.326** (0.13)
Industry patent int.	0.605*** (0.16)	0.608*** (0.16)	0.473*** (0.16)
Exporter	0.337*** (0.11)	0.338*** (0.11)	0.315** (0.11)
Foreign	-0.029 (0.08)	-0.028 (0.08)	-0.031 (0.08)
Innovator * TM intensity		-0.061* (0.03)	-0.059** (0.06)
Innovator * patent intensity		0.023 (0.09)	0.025 (0.11)
R&D/emp			0.142*** (0.02)
MachIT/emp			-0.011 (0.03)
External know/emp			0.018 (0.04)
Train/emp			0.067 (0.15)

Design/emp			-0.072 (0.07)
Market/emp			0.180*** (0.03)
Change			-0.011 (0.03)
Constant	2.813*** (0.43)	2.805*** (0.42)	2.810*** (0.41)
Observations	2634	2634	2634
R-squared	0.63	0.63	0.64

Notes: Dependent variable = log of value added. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sector dummies also included (statistically significant as a group at the 1% level).

Table 15 shows a similar set of regressions, this time with trade mark and patent intensities as the key variables of interest. Regression (1) indicates that firms with higher patent intensity have higher value added, but those with higher trade mark association do not. However, regressions (2) and (3) do not support these findings. Once we link IP intensity with innovators, patent intensity loses any significance. While the trade mark intensity coefficient does become significant, the negative 'innovator' interaction suggests that it is only non-innovators that benefit from higher trade mark intensity. These results appear somewhat inconsistent and counter-intuitive; hence we decided to investigate what might lie behind them:

- We were concerned that the interaction between the individual innovator dummies and the 'any innovator' interaction variable was confusing the results. Hence we ran separate regressions for: only product innovators (n=222), only process innovators (n=442) and both product and process innovators (n=550). The results confirmed that for these samples there were no significant 'trade marking' effects.

- Are the results different for newer firms? We ran regressions for firms less than six years old. Here we found that higher trade mark intensity was associated with higher value added. The coefficient on trade mark intensity was 0.07* in full sample and 0.12* in the innovators only sample.

- We also looked at a sample of small firms with fewer than fifty employees. The only significant coefficient was on trade mark intensity in the innovators only sample (0.15***).

4.1.7. Summing up productivity results

Using regression samples of 35,279 firm-year observations from ARD2, and 2,645 observations from the joint CIS4-ARD2 sample, we have investigated the association between productivity and trade marking. An initial analysis, based on the ARD, suggests that trade markers have a 21% higher productivity. This controls for variables such as firm size, export status and foreign ownership, but it does not control for the extent or nature of innovation, which trade marking may proxy, or for many other company characteristics. For example, when we control for recent advertising the productivity differential for trade markers falls to 7%.

We find that increasing the intensity of trade marking (the number of trade marks per 100 employees) is also associated with better performance. More advanced analysis does reduce the magnitude of these associations. For example, when we control for a 'time invariant, firm specific effect' we find that the association for the intensity of trade marking with productivity falls to about one sixth of its original value.

We next investigated the extent to which trade marking is associated with higher productivity using the CIS4 data. On this much smaller sample we could include variables for whether the firm reported innovation, R&D, marketing, management ability and employee skills. This helps test the robustness of our earlier results on trade marks, but we can only conduct cross-sectional analysis with the CIS4-ARD2 sample. As might be expected, the inclusion of direct measures of innovation from the CIS, together with information about the quality of the workforce, removes the statistical significance of the trade marking-productivity result (although it remains positive). Further analysis suggested it is only newer and smaller firms that received a boost to productivity from raising trade mark intensity, with all the extra variables remaining constant. Even so, the CIS-based analysis helps us to decipher the differences between trade markers and other firms, by indicating that there is a positive correlation between innovation activity and trade marking and that the employment of science graduates improves productivity.

4.2. Employment and wages

A further dimension of the performance of firms in relation to their trade mark activity is their ability to create or sustain jobs. Successful firms may also be able to pay higher wages than less successful companies. Such analysis of employment and wages can also give us metrics to assess some of the benefits to households from innovative activity. Thus if innovative firms create more good jobs, rather than just sustaining low status poorly paid jobs, these are characteristics of innovation that will be of benefit to many households with working members.

The introduction of new technology, or process innovation, can have positive and negative effects on employment. Some jobs will be destroyed by new techniques, while the demand for those with newer skills will tend to rise. At the same time, the introduction of new products into the marketplace, or product innovation, will generally increase the demand for at least part of a firm's output, thus sustaining or increasing employment, though even here the impact on jobs may depend on skill and occupation. Harrison et al.

(2008) conducted a cross-country study using data from four European Community Innovation Surveys to model the general impact of innovation on employment. They estimated that, in 1998-2000, the impact of process innovation was usually very slightly negative for manufacturing but positive for services, although all these impacts were very small in each country. In contrast, their estimates suggest that the impact of product innovation was uniformly large and positive in France, Germany, Spain and the UK.

As with employment, the impact of innovation on wages is hard to predict from economic theory. Some firms enjoying successful innovation and higher profits will choose to share the financial rewards with their workforce; others, especially if financially constrained, may retain these rewards to reinvest in research and development (R&D), or to pay larger dividends to shareholders. An early study by Van Reenen (1996) argued that innovation increased the gap between prices and costs of production (termed economic rents) which led to higher wages. His empirical work on UK data for large firms observed in 1976-1982 demonstrated that 20-30% of such economic rents were awarded to workers.

A fuller survey of these issues and the relevant literature can be found in Greenhalgh and Rogers (2010a). As their survey shows, there have only been a handful of studies using UK company level data to explore the impact of innovative activity on jobs and wages and very little attention has been paid to the role of trade mark activity within these studies.

4.2.1. Trade mark activity and employment

The standard economic approach to modelling how firms choose their level of employment involves assuming that they wish to combine their use of various factor inputs, including labour, capital, raw materials and energy, so that they succeed in producing any given level of output at the minimum cost.[19] The equation determining the demand for workers then depends on the target output, the cost per unit of each factor and the existing technologies. The main input price variables (wages, interest rates, materials costs) are those prevailing in the industry or at a particular time, so are not company-specific. This reflects the fact that each firm has to hire its inputs in the marketplace at factor costs determined by supply and demand. Additionally, using industry level wages to explain employment within individual firms avoids the problem of some company-specific costs being dependent on whether or not the firm is innovating – such as the cost of hiring expensive researchers for R&D.

The basic employment equation is:

$$l_{it} = \alpha_0 + \alpha_1 s_{it} + \alpha_2 w_{jt} + \alpha_3 c_t + \alpha_4 m_{jt} + e_{it} \qquad [5]$$

where *l* is employment within the firm, *s* represents the firm's current sales (turnover), w_j is the industry wage (median hourly earnings excluding overtime), *c* is the (country) cost of capital (measured by the real interest rate), m is the industry cost of materials and all variables are in natural logs. The intellectual property variables that act as proxies for innovation can then be added to this basic equation.

19 An equivalent assumption is that they wish to maximise their production of output for any given level of costs incurred.

If firms are anticipating a rise in orders due to recent innovation, their decision to hire will depend on future sales not just current output. We do not know the level of expected future sales but, as we use current sales as our scale variable, the impact of any expected change in sales due to innovation can be assessed using innovation variables such as trade marks. Innovation variables will also pick up company-specific variation in the number of workers needed to produce a given output, which is influenced by the choice of process and their productivity. Therefore, we cannot predict the total effect of innovation on employment as the respective process/productivity and product/sales effects can offset each other.

The augmented employment equation is as follows:

$$l_{it} = \alpha_0 + \alpha_1 s_{it} + \alpha_2 w_{jt} + \alpha_3 c_t + \alpha_4 m_{jt} + \alpha_5 P_{it-1} + \alpha_6 T_{it-1} + e_{it} \qquad [6]$$

where *P* and *T* refer to the firm's patents and trade mark activity in the previous year. These can be measured either as dummy variables, reflecting any such activity in the firm, or as intensities, reflecting the rate of innovation activity relative to the size of the firm.[20]

As both (5) and (6) are to be estimated using a panel of firms, the question of whether or not to include company fixed effects (f_i) is raised.[21] There are benefits and costs of so doing – without fixed effects any persistent differences between firms that are correlated with an included variable can lead to a biased coefficient. Even so, firms that engage in IP activity are often regular users of patents and trade marks, so we could lose the ability to assess the size and significance of these variables, as the model with fixed effects relies on only those observations with year to year variation in IP activity.

The first example of this approach to modelling UK employment using a range of IP variables as a proxy for innovation was provided by Greenhalgh, Longland and Bosworth (2001). They analysed a panel of large UK production firms for 1987-94, which meant their sample contained no services sector or smaller firms. In that study the impacts of R&D, patents and trade marks were explored with the immediate inclusion of company fixed effects. In the basic regression, this specification made UK trade marks insignificant, but a supplementary regression explaining the size of the company-specific constants (or fixed effects) did reveal persistent differences between firms that were trade marking and those that were not. In what follows we begin with a set of panel regressions that first omit the fixed effects and then include them to observe their impact on the trade mark variable.

20 In this equation, unlike that for value added, we do not include advertising as a proxy for intangible assets, because we already have sales in the equation and this captures much of the effect of recent advertising.

21 In this case the error term e_{it} is partitioned into $f_i + u_{it}$ where f_i is the time invariant firm fixed effect.

4.2.2. Regression results for employment

Having documented the nature of the employment-related variables, we now present our estimates of the employment equation. As with the analysis of value added by the firm, we do so in stages, first presenting OLS estimates of the equation using the pooled dataset of observations across firms and years and then examining alternative specifications. Table 16 shows the summary statistics for the regression sample used for both the employment and wages equations. This sample is very similar to that used for the analysis of value added and covers 2000-2006.[22]

Table 16 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

The basic employment equation (Table 17 col.1) shows that employment is positively related to sales, but negatively related to industry wages (average hourly earnings). Both these variables conform to expectations that firms will hire more workers when demand rises, but will lay off workers when wages rise. From the signs of the coefficients on costs of raw materials (positive), and costs of finance (negative), we can conclude that labour and raw materials are substitutes for each other in the production process, while labour and capital are complementary inputs. This means that when raw material prices rise, firms use more labour to economise on their use. However when the cost of capital investment rises, firms cut back on both capital expenditure and employment.

22 The code for generating the sample was slightly different due to the trimming procedures for extreme values of employment and deletions of observations with missing key variables.

When the trade mark dummy (representing the application for one or more trade marks in the previous year) is added to the basic equation (in Table 17 col.2) it shows a significant positive association with employment. In broad terms, trade mark active firms employed about 20% more workers than inactive firms. It is worth noting that this regression has already controlled for size by the inclusion of company sales as an explanatory variable, suggesting that trade marking firms are considerably more labour-intensive than other firms. However when using this single dummy variable approach for recently acquired IP assets, we find no evidence of higher labour intensity in respect of firms that have recently applied for a patent (Table 17 col.3). Here the coefficient for the patents variable is small and insignificantly different from zero.

Table 17 Pooled OLS employment regressions with IP dummies

	(1)	(2)	(3)
Sales	0.4811*** (0.0105)	0.4734*** (0.0106)	0.4733*** (0.0106)
Industry real wage	- 0.7205*** (0.0498)	- 0.7042*** (0.0493)	- 0.7048*** (0.0494)
Industry materials costs	0.0795*** (0.0072)	0.0777*** (0.0071)	0.0776*** (0.0072)
Real interest rate	- 4.5779*** (0.6065)	- 4.6879*** (0.6049)	- 4.6908*** (0.6053)
TM dummy (t-1)		0.1977*** (0.0274)	0.1970*** (0.0274)
Patent dummy (t-1)			0.0103
Constant	6.6968*** (0.6443)	6.8401*** (0.6433)	6.8448*** (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 in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In Table 18 we investigate whether the intensity of trade mark and patent activity in the firm has any further impact beyond that seen in the simple ‘on-off’ switch of the dummy variable.[23] Considering first trade marks, there appears to be a non-linear relationship between employment and trade mark intensity, as intensity is only significant when both its level and its squared value are included (Table 18 col.3). Taken together with the positive coefficient on the dummy variable for trade mark activity, this quadratic relationship shows a continuing decline in the impact of increasing trade mark intensity on employment, albeit at a flattening rate.[24] This implies that the positive impact of trade mark activity on employment is greater for large firms than for medium and smaller sized firms obtaining the same number of trade marks. This happens because trade mark intensity and patent intensity are inversely related to the size of firms, as shown by Rogers et al. (2007). Broadly speaking larger firms do not increase their patents and trade marks *pro rata*, so IP intensity falls with company size.

With patents, we see a similar story. There is a positive relationship with employment, but one that declines as patent intensity rises.[25] This represents the difference in the impact on employment for any given number of patents obtained by a large firm (smaller intensity, bigger impact) and a small or medium sized firm (higher intensity, smaller impact).

23 In the quoted results all the IP intensities are calculated with respect to employment as was done in the analysis of value added. However we also estimated parallel employment and wage equations where intensities were defined with respect to firm value added. This was done in case any transmission of measurement error in employment was causing biased coefficients to arise. In the event the alternative value added intensities gave rise to the same signs and similar significance levels as those using employment intensities.

24 The coefficients on TM intensity and intensity squared imply a minimum turning point to a positive slope only at an extremely large value of TM intensity, well outside the range of the data. The same is true for the coefficients on patent intensity discussed below. Thus within the range of the data and for a considerable range of values beyond, both of these quadratic functions reflecting the impact of IP intensities are negatively sloped.

25 Although initially we saw a zero impact from the patent dummy variable alone, when we include intensity either linearly or in quadratic form there is a positive but declining impact of patents as intensity rises.

Table 18 Pooled OLS employment regressions with IP intensities

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

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We continued our investigations by exploring regression estimates using fixed effect models. As explained in the productivity analysis (Section 4.1.3), this subtracts the mean values for the firm from both the employment variable on the left of the equation and from all the variables on the right. Thus the model is dependent on observing the relationship between changes at the level of the firm , rather than on those due to persistent differences between firms that play a strong role in the OLS estimation. Table 19 presents the results for fixed effects models for equations that mirror those in Table 17 that used the pooled data without these restrictions. As in the productivity analysis, all the coefficients are considerably lower while the wages variable is now perversely signed and significant.[26]

26 It must therefore be the case that the firms within the database with highest wages also have higher employment, whereas in the cross-section of firms there is an inverse relationship.

Table 19 Fixed effects employment regressions with IP dummies

	(1)	(2)	(3)
Sales	0.0914*** (0.0080)	0.0913*** (0.0080)	0.0913*** (0.0080)
Industry real wage	0.3306*** (0.0557)	0.3319*** (0.0557)	0.3319*** (0.0557)
Industry materials costs	0.0252*** (0.0044)	0.0252*** (0.0044)	0.0252*** (0.0044)
Real interest rate	- 2.0376*** (0.2977)	- 2.0445*** (0.2975)	- 2.0454*** (0.2976)
TM dummy (t-1)		0.0308*** (0.0087)	0.0307*** (0.0087)
Patent dummy (t-1)			0.0053 (0.0158)
Constant	5.9155*** (0.3525)	5.9176*** (0.3523)	5.9186*** (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: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A firm that had not registered any trade marks in one year but registered some in the next year sees a 3% increase in employment, whereas there is no significant impact on employment of registering a patent. The use of trade mark and patent intensity variables in the fixed effects models yielded no significant coefficients, whether entered in linear or quadratic form.

Taken as a whole, these results are compatible. We would not expect to see annual 20% fluctuations in the size of a firm's workforce, whereas an increase of 3% is plausible perhaps after a new product launch. At the same time, we could envisage a firm that is persistently innovative being able to sustain a larger differential in employment than a firm with no innovative products. The latter is by definition constrained to competing on price and would thus be paying much more attention to keeping its costs low by having a lean workforce.

4.2.3. Trade mark activity and average wages

In the economic theory of wage determination many factors determine the average wage paid out by a given firm, but we choose to focus on the firm's position relative to other firms in the industry, rather than trying to model its wage negotiations and settlements from scratch. So, we want to know whether firms that are creating intangible assets, such as trade marks, pay more than other firms in their industry.

By modelling the firm's wages relative to the median industry wage we can effectively ignore many of the factors causing inter-industry wage differentials. However one feature of the firm's characteristics that is well known to affect its rates of pay is its size. Even within a given industry, large firms pay more than smaller firms. Many explanations have been cited for this phenomenon, ranging from the nature of the work (more specialised in large firms) to the relationship between workers and their employer (more convivial in small firms). These features of employment generate what are known as 'compensating differentials' in wages, so that the net returns including all non-pecuniary features of the job are equalised across firms. Thus our basic wage equation includes dummy variables to capture differences in pay associated with size. Another control variable entered in the basic equation is recent advertising expenditure. We have included this to control for the situation where a firm has invested a large amount to publicise its product and has reaped rewards in turnover and profits that it is now sharing with the workers as bonuses.

The basic wage equation is therefore:

$$p_{\mathrm{it}} = \alpha_0 + \alpha_1 w_{\mathrm{jt}} + \alpha_2 z + \alpha_3 a_{\mathrm{it\text{-}1}} + e_{\mathrm{it}} \qquad (7)$$

where p_i is the average annual earnings in the firm, w_j is the industry wage, z is a firm size indicator and a is recent advertising.

There are three main reasons why innovative firms might pay more than average: the possibility of sharing their increased profits from innovation with the workers, the prospect that new techniques of production have made workers more efficient justifying a wage rise, and the likelihood of the firm increasing its rate of hiring better skilled or more experienced workers, who command higher pay. Within our database we are unable to differentiate either of the first two forces from each other or from the third composition effect, as we do not have information about individual worker productivity or the skill composition of the workforce.

The augmented wage equation is then:

$$p_{\mathrm{it}} = \alpha_0 + \alpha_1 w_{\mathrm{jt}} + \alpha_2 z + \alpha_3 a_{\mathrm{it\text{-}1}} + \alpha_4 P_{\mathrm{it\text{-}1}} + \alpha_5 T_{\mathrm{it\text{-}1}} + e_{\mathrm{it}} \qquad (8)$$

An earlier study modelling the impact of intangible assets on wages in this way is that by Greenhalgh and Longland (2001). These authors showed that, for large UK production firms observed in the period 1987-1994, having a higher intensity of trade marks per employee was a significant factor in raising average earnings per person employed.

4.2.4. Regression results for wages

Starting with the basic regression (Table 20 col.1) we see that the firm's annual wage (average annual earnings per worker) follows the industry wage index with a highly significant positive coefficient. This coefficient is however below unity, as there are differences between the dimensions of these variables: the firm's annual wage incorporates variations between firms both in hours worked per year, as well as in the level of hourly wages; while the industry wage is the median hourly earnings index and this may change with the composition of firms in the industry. Both factors will lead to a less than perfect correlation.

The results relating to company size in the basic regression show unexpected differences, as the highest average earnings are seen in the *smallest* firms, albeit wages that are just 0.5% higher.[27] There is no significant difference between large firms and the base group for comparison of medium-sized firms. These rankings by company size differ from the literature on hourly wages, but may simply reflect differences in working hours. Thus smaller firms may expect workers to work longer hours for lower hourly wages. Alternatively, the smaller firms may be employing a different mix of workers to other firms in their industry, and may have more highly qualified workers on their payrolls. As we lack such detailed data, we can only note these as potential reasons but cannot reach firm conclusions.

27 We note that in our sample there is a constraint in the selection of small firms within the raw database and again when we select observations for use in the panel regression conditioning on the firms having several continuous years of data. As a result those selected may not be typical of all smaller firms.

Table 20 Pooled OLS wage regressions with IP dummies

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

Notes: Dependent variable is log of firm annual earnings per employee. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The log of advertising expenditure is positively associated with higher average wages. This is what we would predict, as firms that have achieved market power by strongly promoting their products should earn higher net revenues that can be shared with the workforce. However the effect of rent–sharing from advertising is very small. The coefficient in table 20 col. 1 implies that even a standard deviation increase in log advertising expenditure would only raise wages by 0.2%.But, does the acquisition of intellectual property assets add a further premium to average earnings?

In Table 20, cols 2 and 3 we show the results of adding first the trade mark and then the patent dummy variables. Both are positively associated with the firm's wage, although the level of additional payment made by these IP-active firms to their workers is quite small: around 0.7% for trade marking alone (slightly less when patents are included) and around 1.3% when patenting. These results represent company-level premiums over and above any general industry ones. With very low wage settlements in many sectors today, even these small bonuses could represent a welcome addition to salary. Taken together they imply that a firm that was recently active in both patents and trade marks would be paying an extra 2% on annual wages to its workers. These additional labour costs could represent either the sharing of extra profits arising from intellectual property, or they might arise due to the need to employ higher quality workers to sustain R&D and product development reflected in the acquisition of these IP assets.

Table 21 Pooled OLS wage regressions with IP intensities

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

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 21 contains the regression results when the intensity of IP activity is included. Trade mark intensity shows a very small negative gradient, a similar impact to that observed above for employment. As we know the highest intensities are observed in smaller firms, this negative coefficient implies that trade mark active small firms pass on less extra pay than larger firms. With patent intensity, there is an interesting reversal of this story. Here higher patent intensity is associated with higher pay, so smaller firms either reward their workers more generously or recruit a larger proportion of highly paid workers to engage in the R&D that is producing the patents.

As with the employment functions, we also estimated corresponding fixed effects models for wages. Here we observed no significant impact of either trade mark or patent activity once the persistent differences between firms were eliminated by the fixed effects. This is not surprising as we have observed only small impacts of IP activity in the above pooled OLS regressions and we expect to observe even smaller effects in the FE model. The only interesting statistical finding was that the coefficient on industry wages is now very close to unity, suggesting that the fixed company effects clean out all the variation between firms in hours worked and skill mix that may have been driving the lower coefficient in the OLS regressions. This is not surprising, in that movements in these two characteristics of firms would not be likely to take place rapidly within the six years covered by our database.

4.2.5. Summing up the findings on trade marks, patents, jobs and wages

There is a common assumption in innovation policy circles that creative and inventive firms will help to sustain employment and wages in advanced countries. The view is that firms in high cost production locations that do not innovate will lose market share to import competition, so jobs will 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 limited.

In this section we estimate both an employment function and a relative wages equation at the level of the firm. We demonstrate that employment is significantly higher in firms that are trade mark active, even when we control for the size of the firm, using sales as a proxy. This suggests that the activity of developing and offering new products and brands to the marketplace increases the labour intensity of the firm: they employ more workers. The strength of the association is such that a firm that is persistently trade mark active has a workforce that is one fifth larger than a similar firm that is inactive. However we found no parallel effect of recent patent activity in terms of the firm’s level of employment, sales levels being equal.

In the analysis of the firm's average wages we find a small positive impact of trade mark activity (a 0.7% premium) and a slightly larger positive impact of patent activity (a 1.3% premium). Thus firms engaged in these activities are offering higher average take home pay to their employees than other firms in their industry. We are unable to determine precisely whether this is due to higher hourly wage rates, longer hours worked by each employee, or higher skill levels. Nevertheless, these findings for employment and wages taken together imply that firms that are trade mark and patent active support more 'good jobs'.

4.3 How households benefit from innovation

In this section we draw together several of the results from the previous sections to assess the benefits to a typical household from the innovative activity of firms. Households benefit principally as consumers of innovative products but they may also benefit as workers employed by innovative firms.

The benefits of innovation and the associated use of intellectual property flow through a number of channels. Process innovation lowers costs of production by raising efficiency and productivity, and this ultimately *lowers the price* of the item under production. This price reduction happens at the latest when a patent expires, due to the impact of competitive entry by other firms using the patented technique.[28] However it can occur more immediately if an innovation is imitated or rapidly distributed. This is most likely to occur with areas such as services that cannot always use patents to protect their service process innovations.

Product innovations see firms offering consumers new varieties of products. This is sometimes characterised as a general process of *increasing product quality*. If a new item is produced with more useful and appealing characteristics than its predecessors it may initially be supplied at a higher price. At this stage only the keenest purchasers or early adopters will change to the new expensive item. Generally the price is reduced over time as the supplier attempts to reach a mass market. The result is that a better product is at that stage supplied at a similar price to the earlier, poorer quality item. So the consumer gets more for his money and this can be seen as equivalent to a reduction in unit price, in this way resembling process innovation.[29]

Most often there is more variety and improved quality, as product innovation also offers the buyer a *greater variety of products*. New products may be similar to existing ones but focus on particular combinations of characteristics. Where the set of people with these requirements is small, this is termed a niche market, but, as the number of varieties proliferates, the sum of all the niches can be a large market. Thus we often see larger

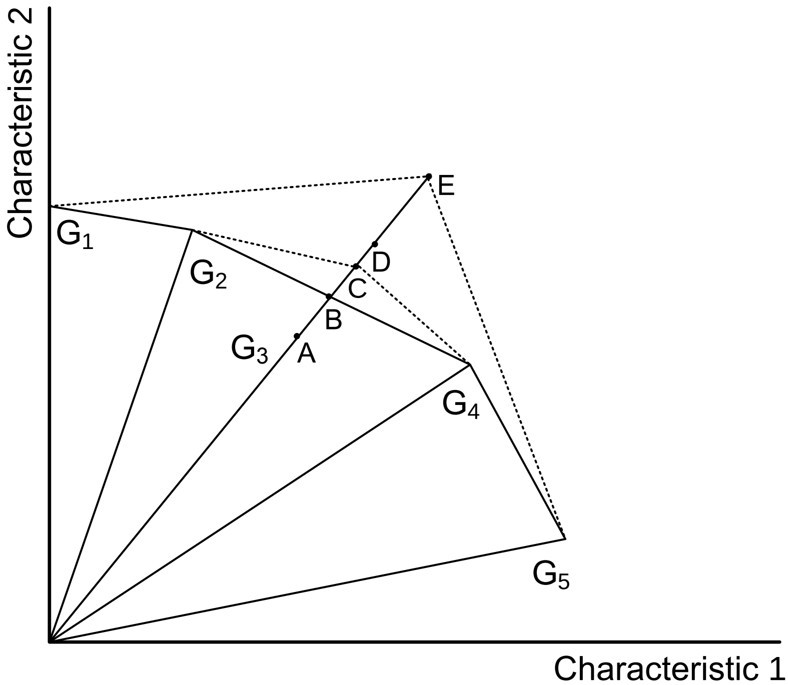
28 See Greenhalgh and Rogers, (2010a) Chapter 1, for illustration of the various types of innovation and their consequences for pricing and consumer demand.

29 Quite often there is a direct link between process and product innovation, whereby a new process allows the design and manufacture of novel products. Also, as argued in Bloomberg (2006) there has been a shift in the focus of innovation since the 1990s. Whereas the focus in the past was on product quality and cost effectiveness, today the emphasis is on reinventing business processes and building new markets that meet untapped customer needs.

producers creating a big portfolio of varieties within the same supply chain, while the same product market also sustains many smaller firms coexisting with this larger firm and supplying further varieties. Whenever the supply of new varieties results in a better fit between customer preferences and product characteristics, consumer satisfaction is improved.

To summarise: innovation leads to lower prices, higher quality and greater variety of products in the marketplace. Consumers gain from all three – lower prices increase their real purchasing power from any given income; better product quality supplied at similar prices to earlier inferior varieties also gives the customer more value for money; and the increased variety of goods and services makes it easier for buyers to meet their product requirements. All these features of innovation can increase the level of satisfaction – or utility, as economists call it. We can integrate the analysis of product and process innovation into a single framework using the Lancaster (1966) model of consumer behaviour. In this framework, households desire the characteristics of the products – what they deliver in consumable services – rather than the products themselves.

Figure 1 Process innovation leading to cost reduction for an existing product



In Figure 1 we draw each product type as a ray from the origin reflecting the combination of desirable characteristics embodied in each product type.[30] Points further from the origin on a given ray are more desirable than points nearer to the origin. If we compare

30 Figures 1 and 2 are drawn from Greenhalgh and Rogers (2010b) but they are derived from Lancaster (1966 and 1971).

the points achievable from a constant level of expenditure then we get an efficiency frontier which describes the maximum amounts of the desirable characteristics that can be obtained for this expenditure. The segmented linear efficiency frontier is obtained by joining points of equal expenditure along each ray. The points on these segments are available for the same cost as the points on each ray using a linear combination of expenditures on two adjacent products. [31]

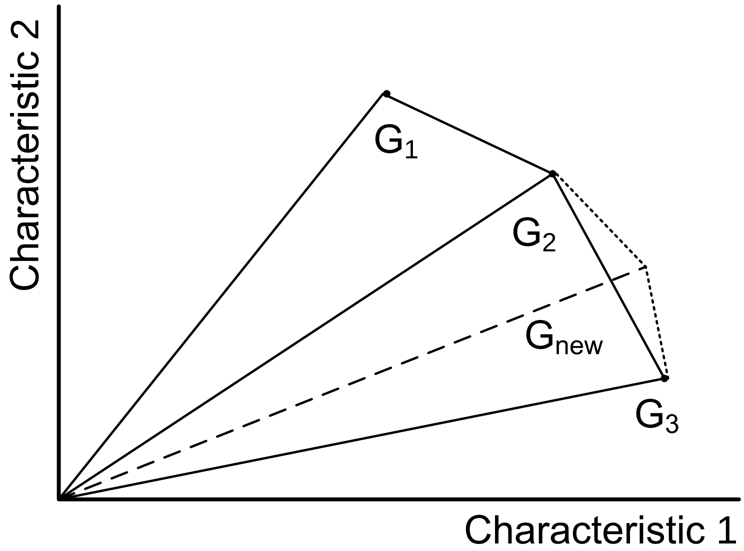
Suppose we focus on car purchases and we rate cars for their fuel efficiency (characteristic 1) and their carrying capacity (characteristic 2). An individual who rates characteristic 1 highly for extensive commuting and weekend motoring may buy product type G_4. Another person who rates carrying capacity highly and focuses less on fuel efficiency may prefer product type G_2. In Figure 1 suppose that one producer achieves a cost-reducing process innovation for his product G_3, which has intermediate proportions of fuel efficiency and carrying capacity. If he were to price the product highly (point A) no-one would switch to his product. At price B his product offers nothing above that available from existing providers of type G_3. However as he lowers his price, passing on some of his cost savings from the innovation, this product is now offering the volumes of characteristics represented at point C, which extends the previous efficiency frontier. Some existing customers, who had been at B, or on the adjacent segments between products G_3 and G_2 or G_4, will switch to buying from the process innovator.[32] It may well be the case for our two car buyers of G_2 and G_4 that they each buy the same type of vehicle, as it offers both fuel efficiency and carrying capacity at a lower unit price than other varieties.

In Figure 2 we illustrate the case where a new variety of a good or service is offered to the market. This is represented by a new ray from the origin labelled G_{new} . This product will appeal to consumers whose preferred taste combinations lay between existing varieties G_2 and G_3. As long as it is priced so that buying the same amount of each of the characteristics 1 and 2 by combining existing products is more costly than what is offered by the new variety, then the efficiency frontier is extended outwards and the new product will successfully enter the market. Some customers will buy only the new item, while others will buy it alongside existing products. The fact that in these two examples of process and product innovation some customers switch part or all of their purchases is sufficient for us to conclude that they are more satisfied – this is the so-called ‘revealed preference’ theory. If they did not prefer their new patterns of purchases then they would, as rational individuals, have remained with their existing suppliers.

31 This requires the products to be divisible in units small enough to permit the frontier to exist without gaps or non-linear segments.

32 If the supplier achieving the process innovation continues to lower his price further to D and finally to E, then eventually the suppliers of G_2 and G_4 will have no customers. This is because when G_3 reaches price E then buying a linear combination of G_1 and G_3 or of G_3 and G_5 is more cost effective than any of the combinations involving G_2 and G_4.

Figure 2 The effect of product innovation



We have discussed the benefits of innovation without specific reference to the role of intellectual property or trade marks. Aside from their role in providing incentives to firms to innovate, trade marks also inform customers. To benefit from innovation consumers need to be able quickly and easily to identify novel products and their prices and learn about their characteristics. How quickly and efficiently the information about the existence and quality of products is transferred to potential consumers affects their levels of satisfaction. Earlier we argued that the registration of a new trade mark can signal a new product variety entering the marketplace. The continued use of a known trade mark can also signal its source and quality. The use of trade marks by firms for signaling product quality and new varieties on offer therefore greatly improves customers' ability to choose. This use of trade marks thus *saves buyers time* which would otherwise have to be spent on sampling products. Similarly, it helps to avoid them wasting money buying unsatisfactory products.

These benefits to consumers apply to any household whether its adult members are working or in retirement. Some households will benefit further if any of its members are employed by an innovative firm. In section 4.2.3 we used employment and wages functions to estimate the relationships between the firm's trade mark acquisitions, its employment and annual average pay of its workers. These showed a large and significant positive association between trade marks and levels of employment, conditional on the firm's current level of sales. Some small positive associations for average pay were also demonstrated.

However, as often occurs in economic analysis, there are conflicting influences to be adjudicated. We noted in our discussions of the employment and wages consequences of innovation that some jobs may be destroyed as new process technology is introduced. This means that there will be some negative outcomes for those working in jobs that are phased out by new technology in innovative firms, and for those working in uncompetitive firms that lose their market share to innovative competitors and eventually close down.[33] Nevertheless, as shown by Harrison et al. (2008) for four European countries, there is evidence that the net job-destroying effects of process innovation are close to zero. The cost-reducing effects of process innovation offer the opportunity for price reductions that cause market share to rise and this largely offsets the job savings that stem from greater productivity. At the same time their estimates of the net job-creating effects of product innovation are strongly positive in both manufacturing and services, contributing from 2.5% to 4% per annum to employment growth at the end of the 1990s.[34] Of course, displaced workers may need to retrain in the new skills to gain work in the expanding occupations.

Another problem identified earlier is that trade marks can be the basis for aggressive brand-building, resulting in market dominance by incumbent firms. In this case, the obstruction of introduction by new entrants of new qualities and varieties of products could reduce market competition. Greenhalgh (2011) documents a number of legal cases where a worldwide brand has chosen to pursue a local company, claiming infringement of its brand name. This has happened even where there was a considerable distance between their product types and no customer confusion was likely to ensue from the continued use of similar marks, so the litigating multinational had no grounds for complaint. Thus in assessing the benefits to households of trade marks we need to ensure that these marks are being used in open competitive markets where the entry and exit of products and firms takes place without extreme dominance by a small number of large firms.

33 Schumpeter called this “creative destruction”.

34 These estimates reflect the net employment effect of product innovation after allowing for substitution of new products for existing products.

5. Trade marking and branding

It is clear that trade marking in isolation is unlikely to generate additional value for the firm. In equation [1] we used *R* to refer to 'intangible capital', which implies firms have made successive (and successful) investments over a period of years. Trade marking will have a role in this process to the extent that it increases the value generated from other investments (such as marketing and advertising).

A brand can be defined as a valuable, well known product or service. Despite our earlier caution about possible anti-competitive effects, Urwin et al. (2008) have argued strongly that branding is important to the UK economy because it involves investment in product design, advertising and marketing. In addition, building a brand involves customer service, reputation building and generating trust in the firm's product or service. It is these investments in intangibles that create brand value over years or decades.

Registered trade marks are only one component in this complex process, perhaps at the start, but potentially throughout the process. A key policy question is how critical trade marks are to the process of building brands. In other words, how do trade-marking and brand building interact?

We have already started to investigate these ideas in previous sections by looking at the interaction between registered trade marks and advertising and marketing. In this section we want to extend this analysis in two ways:

- We confine our analysis to firms with ARD2 data for the entire period 2000 to 2006. This results in a sample of 8,470 firms. We calculate growth of employment and turnover over the period 2003-2006.
- We then use trade mark and advertising from 2000 to 2003 to construct the stocks of these intangible assets held within the firm for 2003 (the initial year of the growth period).

We can then relate each firm's growth during 2003-2006 to its initial stocks of intangible assets. Analysing the growth rates of firms tends to follow Gibrat's methodology. This regresses the growth rate of a factor like employment on the log of the initial value (i.e. log of employment) adding other variables. If the coefficient on the log of employment is negative, larger firms will grow slower than smaller firms. If the coefficient is positive larger firms will grow faster than smaller firms. Gibrat's 'law' asserts that the coefficient should be zero: company growth is independent of company size. There is a large literature on this approach and we follow this here.[35] The basic equation to be estimated is

$$g_{it} = \beta_1 \log(y_{it-1}) + \beta_2 TM_{it-1} + \beta_3 AdvMkt_{it-1}$$

where *g* is growth rate (for employment or turnover), *y* is employment or turnover, *TM* is a stock of trade marks (2000-2003) and *AdvMkt* is stock of advertising-marketing (2000-2003). Additional control variables are also added, including a set of dummies for sectors.

Since growth rates can vary considerably we follow standard practice and exclude growth values above the 99th percentile, or below the 1st percentile, of the growth distribution. The summary statistics for the regression samples are show in Table 22.

Table 22 Summary statistics for growth regressions

Variable	Description	Mean	Std. Dev.
Growth employ	Growth employment 2003-06	0.0702	0.2467
Growth turnover	Growth turnover 2003-06	0.1154	0.4174
Log employ 2003	Log employment in 2003	5.2903	1.5257
Log turnover 2003	Log turnover in 2003	9.3830	1.8566
TM dummy	Trade marker dummy (any 2000-03)	0.1205	0.3256
TM stock	Trade mark stock (15% depreciation)	2.6691	19.191
Log AdvMkt	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 values for growth rates are 0.0156 for employment and 0.0339 for turnover. The statistics in the second panel of explanatory variables are for the n=8470 sample for growth of employment. The n=8410 sample for growth of turnover has some slight differences.

35 For example, see Geroski (1999) and Audretsch et al. (2004) for reviews and Hart and Oulton (1996, 1999) and Koch et al. (2010) for UK studies.

5.1. Employment growth regressions

The results from three employment growth regressions are shown in Table 23. The first regression shows that the coefficient on the log of initial employment is -0.0334. This implies that smaller firms grow faster than larger firms, the other explanatory variables being equal. The economic magnitude of the coefficient is such that a 10% increase in firm size (a 0.1 change in the log value) is associated with a minus 0.003 change in growth rate (or 0.3% fall).

The next variable included is a dummy variable for whether the firm trade marked at any point during 2000 to 2003. The coefficient value is 0.0614, which implies that trade marking firms have a 6% annual growth premium. The regression also controls for age (a negative association with growth), industry levels of trade mark and patent intensity (both have a negative association with growth), exporter status (a negative association with growth) and foreign ownership (no association). A full set of sector dummies is also included.

Table 23 Growth of employment (2003-2006) regressions

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

Notes: Dependent variable = growth of employment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sector dummies also included (always statistically significant as a group at the 1% level).

Columns two and three of Table 23 include the stocks of trade marks acquired by the firm from 2000 to 2003 and the (log of) its cumulative expenditure on advertising and marketing in the same period.[36] Both these stocks are depreciated at 15%.[37] In regression (2) the

36 We did try to use the log of the stock of trademarks but this resulted in poorer results.

37 We also calculated stocks with 30% and 45% depreciation, since there is no information on what

coefficient on trade mark stock implies that an additional ten trade marks (half of one standard deviation) would raise growth by 0.5 percentage points per year.[38] For the advertising and marketing stock a 10% increase (a 0.1 change in the log value) is associated with an increase in annual growth by 0.13 percentage points.

The other coefficients in regression (2) are approximately the same as in (1). There is a slight increase in R^2 (explanatory power). Regression (3) adds an interaction between the trade mark stock and the stock of advertising and marketing. The addition of the interaction term has caused the coefficient on trade mark stock to increase (from 0.0005 to 0.0014). However, the coefficient on the interaction term is negative (-0.0001) and significant, implying that the two stocks are *substitutes*. We might have expected the two stocks to complement each other (since the value of a trade mark stock could be assumed to be boosted by advertising). However, both trade marking and advertising-marketing draw on a firm's limited resources, hence there is an implicit trade-off between the two activities. In any event, the magnitude of the interaction effect is so small that it has very little impact on the net effect of either trade marks or advertising on employment growth.

5.2. Turnover growth regressions

Table 24 shows a similar set of regressions this time with growth of turnover as the explanatory variable. The mean growth rate of turnover is 0.1154 (or 11.54%), which is higher than that for employment growth (0.0702 or 7.02%).

Regression (1) in Table 24 has very similar results to regression (1) in Table 23, with the trade mark dummy indicating trade marking firms are associated with a 6% higher growth rate. However, the coefficients on industry level patent intensity and the exporter dummy are no longer significant.

Regression (2) in Table 24 adds the trade mark and 'advertising and marketing' stocks. As before, these are depreciated at 15%. The coefficient on the trade mark stock is close to that above, but the coefficient on the 'advertising and marketing' stock is more than twice as large. Regression (3) adds the interaction term between the two stocks. Again this is negative, which indicates the two stocks are substitutes. However, as before, the magnitude of the interaction effect is small and the coefficient on the trade mark stock is higher in regression (3) than regression (2).

depreciation rate would be most appropriate. Our regressions using these depreciation rates showed all the coefficients on the stocks were highly significant, and there was little difference in explanatory power. For all stocks we simply used the year 2000 as the starting point (i.e. we did not estimate an initial value). Although we experimented with using standard 'initial year' formula, we felt this was inappropriate in a data set that contains a wide range of firm ages.

38 Even though the standard deviation of the trimmed trademark stock is over 19, this is due to the distribution being skewed; hence an increase in ten is a considerable amount.

Table 24 Growth of turnover (2003-2006) regressions

	(1)	(2)	(3)
Log turnover (2003)	-0.0335*** (0.00)	-0.0571*** (0.00)	-0.0575*** (0.01)
TM dummy (2000-2003)	0.0631*** (0.01)		
TM stock (2003)		0.0006** (0.01)	0.0022** (0.00)
Log Adv Stock (2003)		0.0312*** (0.00)	0.0318*** (0.00)
TM stock x log Adv			-0.0002** (0.00)
Log age (2003)	-0.0703*** (0.01)	-0.0768*** (0.01)	-0.0769*** (0.01)
Industry TMs int.	-0.0516** (0.02)	-0.1182*** (0.03)	-0.1189*** (0.03)
Industry patent int.	-0.0305 (0.02)	-0.0208 (0.04)	-0.0231 (0.04)
Exporter (2003)	0.0172* (0.01)	-0.0050 (0.01)	0.0043 (0.01)
Foreign (2003)	-0.0035 (0.06)	0.0014 (0.01)	0.0019 (0.01)
Constant	0.5650*** (0.05)	0.6960*** (0.06)	0.6977*** (0.05)
Observations	8410	8410	8410
R-squared	0.05	0.06	0.06

Notes: Dependent variable = growth of turnover. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Sector dummies also included (always statistically significant as a group at the 1% level).

5.2.1. Summing up the growth regression results

Our growth analysis is confined to 8,470 firms with ARD2 data for the entire period 2000 to 2006. We calculate growth of employment and turnover for 2003-2006. We then use trade marks and advertising from 2000 to 2003 to construct firm-level stocks for 2003 (the initial year of the growth period). The impact of these stocks on firm growth is then investigated.

For the growth of employment, the analysis shows that trade marking firms have a 6% annual growth premium. As usual, the regression analysis controls for a range of factors including age, industry levels of trade mark and patent intensity, exporter status, and foreign ownership (no association). When we add the stocks of advertising, as well as trade marking, to this regression they are also significant. However, when we interact the stock of trade marks and advertising the coefficient is negative.

For the growth of turnover, the analysis is similar. Trade marking firms have a 6% annual growth premium. The stocks of advertising and trade marking are both significant. But when we interact them, the result is negative if barely so.

What interpretation should we place on this negative interaction effect? It is contrary to our expectations: we assumed that joint trade marking and advertising activity might indicate brand building. Having only four years of data for the calculation of stocks might limit our ability to uncover such synergies. Furthermore, money spent on trade marks cannot be spent on advertising; hence there is an inherent substitution between the stocks. But this negative interaction is good news for consumers, as it gives no strong grounds for interpreting trade marks as being largely devoted to anti-competitive brand building by incumbent firms.

6. Conclusion

The basic starting point for our analysis is the ONS's Annual Respondent Database (ARD2) for the years 2000-2006. The ARD combines information from ONS business surveys over time, covering all large firms but with a sampling frame for smaller firms. To this we added data on each firm's UK and European Community trade marks and patents drawn from the Oxford Firm Level Intellectual Property database, which is a population database for UK firms registered at Companies House. (Further details are in the Data Appendix.)

Using two regression samples of 35,279 firms from the ARD2, and 2,645 from the joint CIS4-ARD2 data, we investigated the association between productivity and trade marking. **An initial analysis, based on the ARD, suggests that trade marking firms have a 21% higher productivity level.** This analysis controls for variables such as workforce size, capital assets, export status and foreign ownership but not for extent or nature of innovation, which trade marking may proxy, nor for a wider range of characteristics of the firm that may affect its trade marking and productivity.

We find that increasing the intensity of trade marking (the number of trade marks per employee) is also associated with better productivity performance. However more advanced analysis, using statistical techniques to control for persistent differences between firms that may be due to other factors, does reduce the magnitude of these associations. We then investigated the productivity associations by using the Community Innovation Survey (CIS4) data. With this data we are able to include variables reflecting reported innovation, R&D spending, marketing, management ability and employee human capital. This acts as a further robustness test for the results on trade marks, although we can only conduct cross-sectional analysis with the CIS4-ARD2 sample. As might be expected, the inclusion of direct measures of innovation from the CIS, together with information about the quality of the workforce, removes the statistical significance of the trade marking-performance result (although it is still positive). **Further analysis suggests it is only younger and smaller firms that received a boost to productivity from raising trade mark intensity**, other things being equal. Even so, the analysis using the smaller CIS sample helps us to decipher the differences between trade marking firms and others, by indicating that there is a positive correlation between innovation activity and trade marking and also showing that the employment of workers with science degrees plays a positive role in productivity performance.

We estimate both an employment function, and a relative wages equation, at the level of the firm. **Employment is significantly higher in firms that are trade mark active, even when we have controlled for the size of the firm using sales**. This suggests that the activity of developing and offering new products and brands to the marketplace increases the labour intensity of the firm. The strength of the association is such that a firm that is persistently trade mark active has a workforce that is one fifth larger than a similar firm that is inactive. However we did not find a parallel effect of recent patent activity in terms of the firm's level of employment, sales being equal.

We find a small positive impact of trade mark activity (a 0.7% premium) on average wages and a slightly larger positive impact of patent activity (a 1.3% premium). Thus firms engaged in these activities are offering higher average take home pay than other firms in their industry. We are unable to determine precisely whether this is due to higher hourly wage rates, longer hours worked by each employee, or a better skilled workforce. Nevertheless, these findings for employment and wages taken together imply that firms that are trade mark and patent active are supporting more 'good jobs'.

The growth analysis is confined to firms with ARD2 data for the entire period 2000 to 2006 and this selection results in a sample of 8,470 firms. We calculate growth of employment and turnover over the period 2003-2006. We then use trade mark and advertising from 2000 to 2003 to construct their stocks for 2003 (the initial year of the growth period). **For employment, the analysis shows that trade marking firms have a 6% annual growth premium**. As usual, the regression analysis controls for a range of factors including age, industry levels of trade mark and patent intensity, exporter status, and foreign ownership (no association). When we add the stocks of advertising, as well as trade marking, to this regression they are also significant. However, when we interact the stock of trade marking and advertising firms the coefficient is negative. **For the growth of turnover, the analysis is similar. Trade marking firms have a 6% annual growth premium**. Both the stocks of advertising, as well as the stocks of trade marking, are significant, but interacting these two stocks produces a negative relationship, though one that is very weak.

This is not what we expected: we assumed that joint trade marking and advertising activity might indicate brand building making these stocks complementary. Having only four years of data for the calculation of stocks may limit our ability to uncover such synergies. Even so, money spent on trade marks cannot be spent on advertising; hence there is an inherent substitution between these stocks. This negative interaction is good news for consumers, as it gives no strong grounds for interpreting trade marks as being largely devoted to anti-competitive brand building by incumbent firms.

In this report we have investigated the statistical relationship between trade mark activity and the performance of firms in four dimensions: productivity, employment, wages and growth rates. **In all these dimensions, the analysis has shown positive correlations between being trade mark active and delivering better performance**. In some dimensions, there were further positive correlations between increasing the trade mark intensity of the firm and performance.

We are cautious about assigning direct causality from trade marks to performance, as many of these results were obtained using a pooled dataset of observations both across firms (cross section) and through time (time series). As the regression data covered only six years, more rigorous panel data methods reduced the observed strength of the positive relationships. We are unable to say whether a longer time series would completely restore the size and significance of the correlations in the pooled dataset. **Nevertheless the observed positive associations indicate that trade mark active firms are different in important and valuable ways from other firms.** This is precisely the hope of policymakers, who design innovation policy to encourage domestic producers to compete on product quality and variety, rather than simply cost and price, and to register ownership of their innovations using the intellectual property system.

Data Appendix

The Annual Respondents Database (ARD) data that we use comes from a stratified, random sample based on the Inter-Departmental Business Register (IDBR). The IDBR covers around 98% of business activity (by turnover) in Great Britain (note that Northern Ireland data is not a component of ARD). The sampling design of the ARD has changed over time with the post-1998 period known as ARD2. For the 2000-2006 period that we use, the survey design was to sample micro firms (1-9 employees) at 25%, firms with 10-99 employees at 50%, firms with 100-249 employees at 100% or <50% depending on industry, and all larger firms (250 plus). See Robjohns (2006) and Barnes and Martin (2002) for overviews of the ARD data.

The observational unit for which the ARD2 surveys information varies according to the structure of the enterprise. In particular, the ARD2 data files have two identification codes: reporting unit (*ruref*) and enterprise unit (*entref*). In the majority of cases, *ruref* and *entref* refer to the same business unit. However, some larger enterprises find it easier to report through several reporting units, hence there can be multiple *ruref* for one *entref*.

In merging in our OFLIP[39] trade mark (and patent) data we use a concordance table provided by the VML between the *entref* identifier and the Company House registered number. The trade mark data refers to the IP activity of the enterprise, meaning our subsequent analysis should be done at the enterprise level. In the 7% of cases where there are multiple *ruref* for one *entref*, we generate a consolidated set of economic data for the *entref* in question by summing across its *ruref*'s.

39 For a detailed description of the Oxford Firm Level Intellectual Property Database, see Helmers, Rogers and Schautschick (2010).

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