Are Advertising and R&D Complements?

PRELIMINARY, PLEASE DO NOT QUOTE

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Abstract

Escalation of advertising or R&D expenditure can give rise to endogenous barriers to entry. This paper investigates whether escalation of investments in R&D raises the return to investments in advertising or vice versa. We provide three empirical tests using a dataset which combines stock market and balance sheet data with information on patents, patent citations, trade marks and trade mark citations from the Internet. Results from Tobin's q regressions show that advertising is a complement to R&D for companies that rely mainly on R&D. R&D is not a complement to advertising for companies relying mainly on advertising. The same results hold in regressions of the gross-profits ratio on R&D to sales and advertising to sales ratios. These results are derived using two stage GMM regressions in which we instrument the ratios using information on patents and trade marks. Finally, quantile regression is used to exclude the possibility that R&D and advertising are complements to a common unobserved variable. We confirm that advertising is a direct complement to R&D for companies relying mainly on R&D.

JEL: L11, L13, O34

Keywords: Advertising, R&D, Tobin's q, Complementarity, Escalation Mechanism, Quantile Regression

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1 INTRODUCTION

Companies competing to improve product quality often resort to advertising and R&D investments. Sutton (1991, 1998) has shown that the level of such investments increases endogenously once markets exceed a certain threshold size. As companies compete for market share, their investments escalate, which forces smaller and less efficient companies to exit the market. As a result the concentration of market shares has been shown to be bounded below. An older literature identified such advertising and R&D investments sunk by incumbents as barriers to entry (Carlton, 2004).

R&D and advertising expenditures are principal means for the escalation which can lead to more concentrated markets. Several recent studies confirm lower bounds to concentration exist in advertising intensive (Robinson and Chiang, 1996; Berry and Waldfogel, 2003) or R&D intensive industries (Marin Uribe and Siotis, 2002) or both (Giorgetti, 2003). Ellickson (2007) identifies investments in distribution as an escalation mechanism for supermarkets.

In this paper we investigate empirically whether advertising and R&D are complementary escalation mechanisms. Cross section data for publicly listed companies, combining financial statement data with extensive information on their patent and trade mark stocks are used. We combine this data to determine whether stock market valuations and gross-profit ratio's show that companies which complement advertising with R&D benefit from this choice. Our research provides no direct test of the presence of endogenous sunk costs. Rather, it provides evidence that investments which constitute endogenous sunk costs are a complement to other investments of the same type.

In particular, we estimate Tobin's q regressions controlling for R&D investments, patent stocks, advertising and trade mark stocks as well as a dummy indicating joint use of advertising and R&D. We extend the analysis of Hall et al. (2005) on the market value of R&D and patents to advertising and trade marks. In their framework we investigate whether the dummy variable indicating joint investments in R&D and advertising is endogenous. This is confirmed for companies that invest in R&D. The endogeneity of the dummy variable shows these companies self select into complementing their R&D investments with advertising investments which significantly increases their market values.

Confirmation of this finding is derived by regressing the gross-profit ratio on advertising to sales and R&D to sales ratio's and a dummy for joint advertising and R&D. The gross-profit ratio is a backward looking maesure of profitability in contrast to market value which is forward looking. The two also differ in that market values are primarily the result of investor's views on future profitability of companies while the gross-profit ratio is a measure of actual profitability. Since advertising and R&D investments are likely endogenous in a cross-section regression explaining the gross-profit ratio (Schmalensee, 1989) we use instrumental variables regression. Instruments for advertising are derived from patent and trade mark data. Using two stage GMM we show that gross-profit ratio's were between 3% and 4% higher for companies combining R&D with advertising than for those relying solely on R&D.

By testing for the same effect using a forward and a backward looking measure of companies' success we are more confident of its robustness. However neither of these findings itself proves that advertising investments complement R&D investments. In fact theory suggests that the finding could be the result of decreasing returns to scale in advertising and R&D investments. As the models set out in Sutton (1991, 1998) do not address the complementarity of different escalation mechanisms we extent a model derived from Sutton (1998) to two escalation mechanisms. It is shown that advertising and R&D investments will coincide as soon as there are decreasing returns to scale to such investments. This seems utterly plausible.

Therefore we turn to quantile regression to investigate the complementarity of advertising and R&D in greater depth. Quantile regression allows us to distinguish settings in which advertising and R&D investments just coincide from those in which they are complements. Arias et al. (2001) suggest using quantile regression to uncover existence of an unobserved complementary factor. We follow their approach to test whether the apparent complementarity between R&D and advertising for companies which undertake R&D is due just to decreasing returns, an unobserved complement[1] or real complementarity. Using a test suggested by Koenker and Xiao (2002) for location and location-scale shifts we show that there is no evidence of unobserved factors which are complements to advertising and R&D when we estimate Tobin's q regressions. We also provide additional evidence for the complementarity of advertising and R&D for companies investing in R&D using this test.

The complementarity of advertising and R&D would have implications for companies' strategy and for policy analysis. Those companies not taking advantage of such complementarities might face competitive disadvantages in the long run. Policy analysis of patents, trade marks or indeed any other policy instruments affecting R&D and advertising would be misleading if important complementarities between R&D and advertising exist, but are ignored. For instance, current economic theory on patents does not incorporate effects of advertising (Scotchmer, 2005).

It might be doubted that there is any significant overlap between R&D and advertising intensive industries. Robinson and Chiang (1996) who test the model of Sutton (1991) provide evidence in passing for coincidence of high advertising and R&D expenditures using the PIMS database. Our dataset shows the distribution of the advertising to R&D investment ratio to be bimodal with significant numbers of companies investing in both with roughly equal intensity. 60% of companies in our sample engage in both advertising and R&D. Only 14% of companies in the sample show no evidence of advertising activity at all. Both advertising and R&D activity are measured using data from companies' income statements or registered intellectual property rights.

This raises the question whether there is always scope for joint escalation of advertising and R&D expenditures. Advertising will almost always matter for companies as the construction and protection of brand names is essential for any company wishing to do business in markets that are not purely local (Wilkins, 1992). In contrast, the possibility for R&D to affect competitive outcomes depends on the degree to which technology can affect competitive conditions. Service intensive or retail industries may be the most obvious examples for low R&D intensity. In conclusion, advertising and R&D investments may have asymmetric potential for escalation and therefore may be complements in only some industries.

The following section discusses the relationship of advertising and R&D more closely. In Section 3 we provide descriptive evidence of the relationship between advertising and R&D. We show that the advertising to R&D investment ratio is bimodal in our sample and provide evidence that higher R&D spending is usually accompanied by higher advertising outlays. Section 4 contains a detailed discussion of our data and the construction of variables we use. Then Section 5 provides results from the market value, gross profits regressions and tests based on quantile regression. Section 6 concludes.

[1] The apparent complementarity of advertising and R&D may be due to unobserved heterogeneity. Unobserved factors that jointly affect advertising and R&D investment decisions may exist. Athey and Stern (1998) and Miravete and Pernias (2006) propose methods with which to disentangle the complementarity of observables from effects of unobserved heterogeneity.

2 R&D AND ADVERTISING

This section briefly reviews the engodenous sunk cost model presented by Sutton (1998, 2007). We show that two outcomes are possible: advertising or R&D by themselves are more effective escalation mechanisms or if decreasing returns to scale are sufficiently strong a combination of both is most effective. In the first type of case companies will invest only in one type of sunk cost in the second we will observe both together.

We adopt a three stage model of entry and sunk cost investments as set out in Sutton (1998). This is extended to two types of endogenous sunk costs. In this model firms first choose whether or not to enter a market, then determine R&D and advertising outlays and finally choose output levels under Cournot competition. We focus on the case in which each firm just produces a single product.

The model is based on a linear inverse demand curve which allows for imperfect substitutability (ρ) of companies' products:

$$p_i = 1 - \frac{2x_i}{u_i^2} - \frac{\rho}{2}\sum_{k=1}^{N-1}\frac{x_{-i}}{u_{-i}} \tag{1}$$

where $(u_i \geq 1)$ represents product quality as perceived by consumers and (x_i) the quantity supplied by each company. Companies' profits net of fixed outlays (V_i) depend on market size (S) and the levels of advertising and R&D investments which companies undertake to raise the perceived quality of their goods:

$$V_i(v_i, w_i, N) = Sp_i(N)x_i(N) - \epsilon v_i^{\varrho} - \gamma w_i^{\mu} \quad , \tag{2}$$

where (v_i) is R&D investment and (w_i) is advertising investment. Advertising and R&D investments affect the level of product quality positively as follows:

$$u_i = F(v_i, w_i) \quad \text{where } \frac{\partial F}{\partial v_i} > 0 \quad \text{and} \quad \frac{\partial F}{\partial w_i} > 0 \quad . \tag{3}$$

If advertising and R&D investments are also strategic complements in the sense of Topkis (1978); Milgrom and Roberts (1990); Vives (1990) then a further property will hold:

$$\frac{\partial^2 F}{\partial v_i \partial w_i} > 0. \tag{C}$$

Following Sutton (1998) profits of each of N symmetric companies, offering the same quality level u, are:

$$S\pi = \frac{Su^2}{2\left[2 + (N-1)\rho\right]^2} \quad . \tag{4}$$

Sutton (1998) argues that two properties characterize any stable equilibrium configuration of quality levels:

i) The viability property: companies enter as long as profits cover their endogenous fixed costs;

ii) The stability property: there is no possibility for a company to enter the market by adding a further product of much higher quality than those already on offer.

These properties can be combined to derive an expression for the lower bound on the one-firm concentration level (C_1) in a market.

Our interest here is to determine whether firms will do better in equilibria in which they invest in advertising and R&D jointly. We show that as long as product quality u depends on advertising and R&D investments and there are strong decreasing resturns to scale in both types of investments, then companies will do better by investing in both simultaneously. However there are cases of weak decreasing returns in which companies invest either in advertising or in R&D.

Consumers will prefer products of higher quality all else being equal. Then the equilibrium with the highest common level of quality $\bar{u} = F(\bar{v}, \bar{w})$ in which all companies remain viable is the solution to the following constrained optimization problem:[2]

$$\mathcal{L}(v, w, \lambda) = F(v, w) - \lambda(S\pi - \epsilon v^{\varrho} - \gamma w^{\mu}) \tag{5}$$

The first order conditions characterizing the solution to this problem are:

$$\frac{\partial \mathcal{L}}{\partial v} = \frac{\partial F}{\partial v}\left(1 - \lambda S \frac{\partial \pi}{\partial F}\right) + \lambda \epsilon \varrho v^{\varrho - 1} = 0 \tag{6}$$

$$\frac{\partial \mathcal{L}}{\partial w} = \frac{\partial F}{\partial w}\left(1 - \lambda S \frac{\partial \pi}{\partial F}\right) + \lambda \gamma \mu w^{\mu - 1} = 0 \tag{7}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = S\pi - \epsilon v^{\varrho} - \gamma w^{\mu} = 0 \tag{8}$$

In Appendix B we show that the solutions to these first order conditions constitute a local maximum if decreasing returns are sufficiently strong. This is an interior maximum as companies invest both in advertising and R&D. Combining the first order conditions above ((6) and (7)) we can show that the ratio of investment in advertising to investment in R&D depends on relative costs and benefits of the investments:

$$\frac{\partial w}{\partial F}\frac{\partial F}{\partial v} = \frac{\epsilon \varrho v^{\varrho - 1}}{\gamma \mu w^{\mu - 1}} \tag{9}$$

It is important to note that the proof that the extreme point characterized by this solution is a maximum does not depend on the number of companies. Therefore we can focus our attention on the stability of the equilibrium against entry by a high spending company that also invests in advertising and R&D and ignore the case in which the entrant invests only in one type of sunk cost. It is also important to note that complementarity of advertising and R&D has no effect on the primary result here - it still remains optimal to combine advertising and R&D if there are decreasing returns to scale. It may also be optimal to combine both if there are increasing returns and the compementarity is sufficiently strong however.

The equilibrium characterized by the solution to the optimization problem we have analyzed here is stable only if the stability condition is also satisfied:

$$V_i(\kappa \bar{v}, \kappa \bar{w}, 1) < 0, \text{ where } \kappa > 1 \quad . \tag{10}$$

This inequality states that a single company choosing some level of quality which is κ times

[2] We are implicitly treating the number of companies as a continuous variable here as we assume that companies always make exactly zero profits. This can be thought of as an approximation that simplifies the argument.

greater than that of the companies in the equilibrium in which N companies provide quality ($\bar{u}$) cannot make positive profits by replacing all of these companies.

Our results imply that we cannot conclude that coincidence of investments in advertising and R&D provides evidence that these investments are strategic complements. To show that advertising and R&D are complements we must provide strong evidence that marginal returns to one type of investment increase as the other type of investment is intensified.

3 DESCRIPTIVE ANALYSIS OF COMPANY INVESTMENTS

This section provides descriptive evidence on the distribution of R&D and advertising investments of 2093 publicly listed companies that have registered either patents or trade marks in Europe. In this sample most companies rely mainly on either advertising or R&D. While this might suggest that R&D and advertising are substitutes the data do not show clear evidence supporting this interpretation. Rather, we find evidence that an important group of companies relies heavily and equally on both types of investment. Additionally, we find that companies using both types of investments invest more in R&D and advertising than companies that use only one of these types of investment. These results support the view that advertising and R&D may be complements.

Our data combine information on publicly listed companies from Reuters, data on patenting activities at the European Patent Office (EPO) and trade mark applications at the Office for the Harmonization of the Internal Market (OHIM), the European trade mark office. We focus on companies that file trade marks or patents with either of these two offices.

Table 1: Company Types and Investments in Advertising and R&D

Investments used	**Companies**	$\frac{\text{R\&D}}{\text{Sales}}$	$\frac{\text{Patent Stock}}{\text{Sales}}$	$\frac{\text{Advertising}}{\text{Sales}}$	$\frac{\text{Trade Mark Stock}}{\text{Sales}}$
Advertising	528	0.000	0.000	0.054	0.003
Both	1,273	0.154	0.017	0.056	0.006
R&D	292	0.060	0.008	0.000	0.000
Total	2093	0.102	0.011	0.047	0.004

Due to the combination of these diverse data sources we have to engage with the problem of unobservables. Not all companies report R&D and advertising activity in their annual reports. Similarly not all companies protect their intellectual property through the EPO or OHIM. By combining evidence on investments and property rights we classify companies into three groups: those that rely exclusively on R&D and patents, those that rely exclusively on advertising and trade marks and those that combine these instruments to further their business interests. Absence of both R&D investments and patents is interpreted as evidence that a company makes little use of R&D relative to advertising and vice versa. Table 1 shows that 60% of companies in the sample make use of both advertising and R&D.

More importantly Table 1 illustrates that R&D investments are significantly higher amongst companies that also use advertising than amongst those that do not.[3] Similarly the ratio of patent stocks to sales is significantly higher for companies that also rely heavily on advertising. In contrast advertising levels appear to be indistinguishable between companies that engage in R&D and those that focus on advertising. However, the ratio of the trade mark

[3] A t-test reveals this difference to be significant at the 1% level.

stock to sales for companies which also undertake R&D is twice that for companies which just advertise.[4] These patterns suggest that advertising and R&D may be complements.

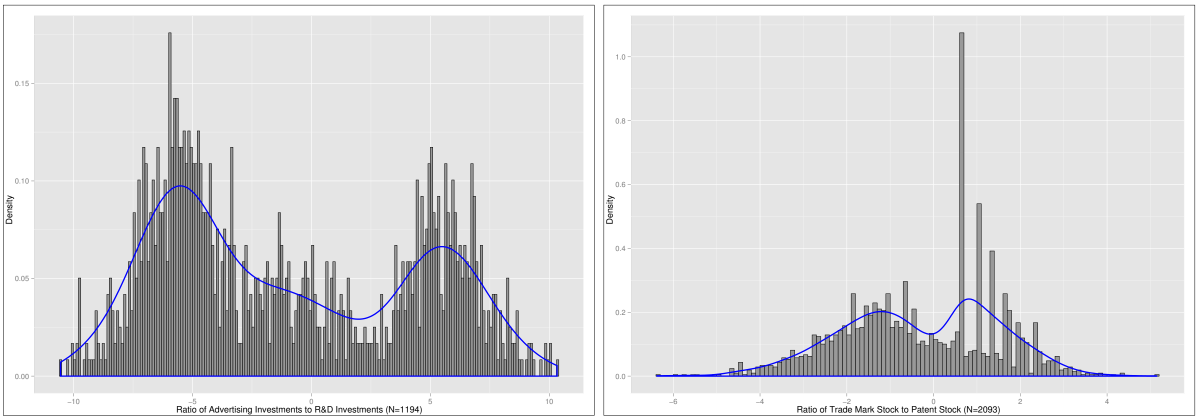

Figure 1: Based on 2093 companies that have registered trade mark or patent stocks in Europe. The number of companies included in each histogram is provided below the panel. In the left panel we exclude all companies that provide no data on advertising and R&D investments. We plot the ratios $\log\left(\text{Advertising}+1\right)/\log\left(\text{R\&D}+1\right)$ and $\log\left(\text{Trade Mark Stock}+1\right)/\log\left(\text{Patent Stock}+1\right)$.

Now consider histograms of the ratio between advertising and R&D expenditures and between stocks of IP presented in Figure 1. These provide more detailed evidence on the intensity of advertising and R&D efforts. The histogram of the log advertising to log R&D expenditure ratio is bimodal. The histogram of companies' relative stocks of intellectual property rights confirms this bimodal distribution of companies' activities.

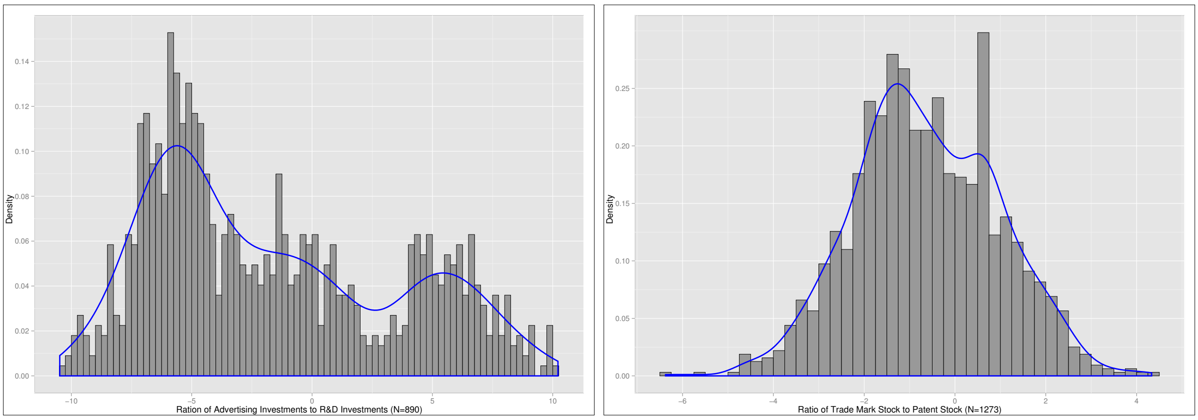

Figure 2: Based on 1273 companies that have registered trade mark or patent stocks in Europe and that make joint use of R&D and advertising.

Figure 1 shows why previous research on endogenous sunk costs focused either on advertising or on R&D intensive companies: most companies tend to invest more heavily in either R&D or advertising. This finding makes it less likely that advertising and R&D are complements. Since 40% of our data is comprised of companies that use only advertising or

[4] This difference is also significant at the 1% level.

Figure 3: Relative investment levels, relative IP stocks and relative IP citation stocks. The top panel sets out the logarithms of R&D to sales and advertising to sales ratios by company. The middle panel contains patent stocks to sales and trade mark stocks to sales ratio's. The bottom panel contains patent citations to sales and trade mark citations to sales. Each panel also contains a trend and the confidence interval for that trend.

R&D we exclude these companies from the data to see whether the distribution of companies' investments is still bimodal. Figure 2 confirms that substantial differences in the way companies mix advertising and R&D remain if we narrow the focus to companies that invest in both advertising and R&D.

While these histograms show that most companies favour either advertising or R&D even if they make use of both, there are clearly at least two if not three levels of the preferred mix of advertising to R&D. All histograms presented so far hide the absolute level of investment in R&D and advertising for a given ratio. Therefore it is impossible to ascertain whether a ratio of advertising to R&D investment is commensurate with different absolute levels of investments. These histograms do not show whether more investment in R&D is associated with more investment in advertising, as would be the case if both were complements.

Table 2: Patent and Trade Mark Stocks by Industry

Business Sector	**Patent Stocks**	**Patent Stock - Sales Ratio**	**Trade Mark Stocks**	**Trade Mark Stock - Sales Ratio**
Industrial Conglomerates	411.854	**0.02225**	**31.565**	0.00157
Automobiles	80.689	**0.01631**	11.222	0.00104
Biotechnology	72.277	**0.01038**	**18.951**	**0.00348**
Personal & Household Products	60.972	0.00628	**65.945**	**0.00797**
Chemicals	58.949	**0.01289**	**19.358**	**0.00297**
Cyclical Consumer Products	54.761	0.00806	9.846	**0.00420**
Technology Equipment	54.708	0.00997	3.753	0.00121
Industrial Goods	33.431	**0.01114**	4.713	0.00205
Healthcare Services	20.542	0.01013	3.667	0.00172
Software & IT Services	16.788	0.00166	4.220	0.00109
Telecommunications	9.986	0.00048	2.057	0.00022
Energy	9.460	0.00112	10.645	0.00110
Industrial Services	7.713	0.00257	1.928	0.00080
Food & Beverages	7.006	0.00135	**11.872**	**0.00315**
Applied Resource	6.174	0.00254	3.835	0.00187
Mineral Resource	4.480	0.00094	0.411	0.00017
Utilities	1.297	0.0004	1.263	0.00010
Food & Drug Retailing	1.040	0.00071	1.260	0.00061
Transportation	0.804	0.00024	0.907	0.00035
Banks	0.664	0.0004	1.516	0.00054
Insurance	0.563	0.0001	0.667	0.00005
Retailers	0.404	0.00027	3.176	0.00143
Cyclical Consumer Services	0.328	0.00015	2.597	0.00068
Real Estate	0.230	0.0002	0.591	0.00040
Investment Trust	0.137	6E-05	0.538	0.00016
Total	22.287	0.00444	6.104	0.00145

Next we provide scatterplots of companies' absolute investments in advertising and R&D. The panels of Figure 3 set out advertising and R&D intensities, patent and trade mark stock intensities as well as patent citation stock and trade mark citation intensities. We distinguish between three types of firm: those that invest only in R&D (pink), only in advertising (blue) and finally those investing in both (green). The graphs are jittered and contain univariate regression lines and their 95% confidence intervals (grey). Figure 3 shows companies with greater patent stocks also tend to have greater trade mark stocks. More remarkably companies whose patent stocks are cited more frequently also hold trade mark stocks that receive more citations through Google. In contrast, the top panel provides no clear evidence that R&D and advertising investments are complements.

These results indicate that there is a complementarity between R&D and advertising efforts with companies that invest more successfully in R&D as measured by patent citations also owning brands that command more attention on the Internet as measured through Google citations to these brands. Figure 3 does not allow us to establish whether advertising and R&D are generally complements or whether this is an industry specific phenomenon.

Table 2 provides patent and trade mark stocks as well as their intensities for twenty five industries.[5] The table is ordered by the level of the average patent stock in an industry. In the remaining three columns we highlight those five industries with the highest average values.

Out of the top five industries with highest patent intensity two also belong to the top five with the highest trade mark intensity. All industries characterised by high patent intensity are also characterised by high levels of trade mark intensity. In contrast there are two industries with high trade mark intensity which have quite low patent intensities: Food & Beverages and Retailers.

This suggests that trade marks are an important complement to patents but that patents need not be a strong complement to trade marks. To provide firmer evidence for this finding we turn to a multivariate analysis of the relationship between advertising and R&D next.

4 DATA

Here we describe the dataset used in this paper. We provide descriptive statistics and discuss the construction of variables.

Our dataset is based on several data sources. Accounting and financial measures were obtained from Reuters. Companies' portfolios of trade marks are derived from the community trade mark register (CTM) that includes all pan-EU trade mark rights registered at the Office for the Harmonization of the Internal Market (OHIM). Our patent data are based on the patent register of the European Patent Office (EPO). [6] Additionally, we use patent citations as a measure of patent value (Trajtenberg, 1990; Lanjouw and Schankerman, 2004). Patent citations were provided by Dietmar Harhoff and are derived from the PATSTAT database. Finally, we use Internet citations to trade marks from Google to capture variation in trade mark values.

To build firm-level patent and trade mark portfolios, both the trade mark applicants of the OHIM database and the patent applicants of the PATSTAT database were matched to company names from the Reuters database. To consolidate our data at the corporate level, we employed the name of each company in the sample and used this string as a search pattern to match all appropriate patent and trade mark applicants. We also used information from the Derwent innovation index and from our own previous work to consolidate companies von Graevenitz et al. (2007, 2008).

We were able to obtain financial data on more than 5000 listed companies worldwide. Of these 2093 registered at least one patent with the EPO or a trade mark with OHIM. These com-

5 Since we obtained accounting and financial measures from Reuters, we used the Reuters Business Sector Scheme included therein to distinguish between industries.

6 The patent data were extracted from the October 2007 version of the PATSTAT database. This is the EPO Worldwide Patent Statistical Database which is available under license from the OECD-EPO Task Force on Patent Statistics.

panies make up our sample. They have more employees, more assets and have higher levels of sales than the average company in our set of listed companies. We focus on companies which registered intellectual property in Europe. This allows us to use information from the patent and trade mark registers to describe companies' behaviour in greater detail.

Table 3 below sets out descriptive statistics for the main variables we employ in regressions presented in the following section. Each variable is discussed in greater detail below.

Table 3: Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Median	Maximum
log Tobin's Q	0.790	0.345	0.150	0.729	2.076
log R&D investment	2.207	3.034	0.000	0.000	10.482
log Patent Stocks	1.935	1.888	0.000	1.549	8.529
log Patent Citations	1.666	1.865	0.000	1.123	7.960
log Advertising	1.651	2.697	0.000	0.000	10.216
log Trade Mark Stocks	1.623	1.289	0.000	1.386	6.382
log Google citations	4.637	7.021	0.000	0.000	21.376
log Assets	7.946	1.352	4.729	7.732	13.396
log Sales	7.877	1.198	0.000	7.683	12.344
Joint Investment Dummy	0.608	–	0.000	1.000	1.000
Seniorities Dummy	0.332	–	0.000	0.000	1.000
Technology area concentration	0.115	0.229	0.000	0.000	1.000
Nice class concentration	0.110	0.223	0.000	0.000	1.000
United States	0.533	–	0	1	1
Japan	0.219	–	0	0	1
United Kingdom	0.048	–	0	0	1
China	0.045	–	0	0	1
Canada	0.040	–	0	0	1
Taiwan	0.029	–	0	0	1
Germany	0.024	–	0	0	1
Australia	0.022	–	0	0	1
France	0.020	–	0	0	1
Hong Kong	0.020	–	0	0	1

Accounting data

The accounting data we use comprise: market capitalisation, sales, total assets, total debt, R&D investment and advertising expenditure. These variables are drawn from financial statements for 2007 as reported by Reuters. Market capitalisation was measured as close as possible to December 31, 2007. To arrive at consistent Euro values, measures denoted in US dollars were converted at the corresponding exchange rate.

Tobin's q The dependent variable in the market value equation is computed by using both accounting and financial measures as Tobin's q is defined as the ratio of the market value of the company to the replacement cost of the company's assets (Hayashi and Inoue, 1991). The computation of Tobin's q is shown in equation (11). The replacement cost of a company's assets is measured using the value of total assets drawn from the balance sheet. The market value of a company is the sum of the market capitalisation, MC, and the market value of its debt, MD. However, as the market value of a company's debt is difficult to observe and estimate (Hall and Oriani, 2006; DaDalt et al., 2003), it is usually proxied by total debt as reported in the balance sheet.

$$\frac{V_t}{A_t} = \frac{MC_t + MD_t}{A_t} \tag{11}$$

R&D and Advertising Measures R&D investments and advertising expenditures are not capitalized in balance sheets. Instead, such investments are treated as expenditures and will be reported as expenditures in companies' income statements in the year in which they occur. To arrive at estimates of capitalized investments, researchers regularly apply the declining balance formula to estimate these investment stocks based on past and present expenditure (Hall, 1994; Hall et al., 2005). Using these annual flow measures and applying the conventional depreciation rate of 15% we compute R&D stocks, R^{stock}, and advertising stocks, M^{stock}:

$$R^t_{stock} = R^t_{flow} + (1-\delta)R^{t-1}_{stock} \qquad M^t_{stock} = M^t_{flow} + (1-\delta)M^{t-1}_{stock} \tag{12}$$

Due to depreciation, past expenditures affect the stock less than present expenditures. The reason for assuming a depreciation of these expenditures is that, similarly to patents, technological knowledge becomes obsolete over time. Regarding advertising expenditures we observe that brands are constantly advertised to maintain awareness. Therefore, we treated R&D and advertising stocks symmetrically.

The market value of a company at a specific point in time reflects expected future cash flows that investors estimate based on the current assets of the company. Knowledge assets and brand equity typically accumulate over a long time. Therefore, all available R&D and advertising expenditures from earlier income statements than 2007 were obtained from Reuters in addition to the expenditures shown in the income statement of 2007.[7] Recall that the declining balance formula needs uninterrupted histories of expenditures. However, as some companies did not fulfil this requirement of continuous time series, the computation of the stocks for these companies would have been inconsistent. Thus, we reset the stocks of these companies to zero. For these observations and all others where R&D and advertising expenditures were not available, a dummy variable was generated that takes the value one when the R&D stock and advertising stock, respectively, is zero or not available.

The recursive nature of the declining balance formula requires an initial stock. As the full history of previous expenditures was not available, the initial stock for the first available observation year of expenditures was computed assuming that the expenditures have been growing at a constant annual rate, g, of 8% prior to the observed time series of expenditures. This allows computation of initial stocks as shown in equation (13) (Hall and Oriani, 2006; Hall et al., 2007):[8]

[7] As the annual R&D and advertising expenditures required were from different years an inflation adjustment was performed to arrive at consistent real 2007 prices. To do this, the GDP price deflator available in Ameco, an annual macro-economic database provided by the European Commission, was used.

[8] Hall et al. (2007) argue that such an approximation of initial stocks has negligible effects.

$$R^0_{stock} = \frac{1}{\delta + g} R^0_{flow} \qquad M^0_{stock} = \frac{1}{\delta + g} M^0_{flow} \tag{13}$$

Intellectual Property Measures

Patents Our patent data record patenting activity consistently before 2006 due to lags in the patent application procedures at the EPO (von Graevenitz et al., 2007). We compute patent stocks with a declining balance formula shown in equation (14). The application of the formula to patent stocks is based on the belief that technological knowledge becomes obsolete with the passage of time reflected in the depreciation rate, δ. As is customary we adopt a depreciation rate of 15% (Hall, 1994; Hall et al., 2005). Unlike R&D and advertising stocks, we observe the full history of both companies' annual patent applications.

$$P^t_{stock} = P^t_{flow} + (1 - \delta) P^{t-1}_{stock} \tag{14}$$

Patent Citations Patent values have been found to be highly skew (Lanjouw, 1998; Harhoff et al., 1999, 2003). To control for the value of patents, we employ patent citations. In the same way, later research studies cite older work, the patent examiner at the EPO adds references to older patents during the examination process. Research that connects patent citations to companies' market value shows that patents which attract more citations, are of higher value (Trajtenberg, 1990; Lanjouw and Schankerman, 2004; Hall et al., 2005). Again, the declining balance formula is used to compute patent citation stocks C^P_{stock}. We weight each of the $\hat{P}$ patents entering the stock at time t by the number of the citations it collects when it is added to the citation stock, c_ρ. Specifically, we deem a three year period sufficient, recording only those citations arriving within this window after publication of the search report (Marco, 2007).

$$C^{P,t}_{stock} = C^{P,t}_{flow} + (1 - \delta) C^{P,t-1}_{stock} \quad \text{where} \quad C^{P,t}_{flow} = \sum_{j=1}^{\hat{P}_t} c_{\rho,j} \ . \tag{15}$$

Trade Marks We use the same trade mark dataset as von Graevenitz (2007) and Sandner (2008). This dataset comprises trade mark applications at the Office for the Harmonization of the Internal Market (OHIM) which began operating in 1996. Little is currently known about the time it takes to build a brand. We adopt a conservative stance and base our trade mark stocks on trade marks registered as a CTM and based on a previous trade mark registration in Europe. Such trade marks are based on what is called a seniority (Phillips, 2003; Council, 1993). Trade mark stocks based on seniorities capture only those trade marks which are well established in one or more European countries. In our dataset there are 3393 such trade marks which are based on 8 previously registered trade marks on average. Our data contains all trade marks which were filed at OHIM before 2005 . While it would be desirable to have data after this date, the problem is mitigated by the fact that the number of trade mark applications at OHIM based on seniority rights has decreased substantially since 1996.[9]

[9] In 1996, the first year when filing of CTMs was possible, 29.9% of all CTM applications claimed seniorities. In 2004, the last year of trademark data available to use, only 4.8% of all filings claimed seniorities. As the level of filings remained fairly constant, the number of applications that claimed seniorites gradually

We do not apply the declining balance formula to trade mark stocks. A positive depreciation rate would imply that trade marks become obsolete as time passes. Trade marks are indefinitely renewable and often exist for decades, in some cases even outliving the companies that created them (da Silva Lopes, 2007). The more a trade mark is used the more valuable it becomes. Trade marks that are applied in the course of trade are not surpassed by newer vintages of trade marks as is the case with patents, nor will rival companies generally manage to dilute them, by creating similar trade marks. Vigilant trade mark owners can prevent dilution by opposing their rivals' new trade marks (von Graevenitz, 2007). Therefore, we assume that trade marks do not depreciate.

$$T^t_{stock} = T^t_{flow} + T^{t-1}_{stock} \tag{16}$$

Google Citations to Trade Marks In order to capture variation in the value of companies' trade marks we weight them using citations to the trade mark on Google.[10] Google lists those web pages that contain the term of the search query. Moreover, Google indicates the number of results that matched the search query. This is our measure of Internet citations. The measure is restricted to trade marks containing words. For each trademark in the corporate portfolios, we used the trademark name as the search query to obtain the number of Internet citations. Obtaining this measure for thousands of trademarks turned out to be a rather lengthy process. We began this procedure in the end of January 2008 and ended it at the beginning of April 2008.

This measure of trade mark value is inspired by measures of patent citations. Trade marks that are more widely known will be referred to more often on the Internet. These references may originate from the manufacturer of marked products, from customer reviews, from the press, and also from bug reports. Although positive and negative references cannot be separated from one another, they still indicate the impact of the trade mark. As the awareness of brands is a main driver of their value (Aaker (1991)), we argue that Internet citations reflect the awareness of a brand and, thus, should be associated with their value.

Similarly to patent citations, we computed a trade mark citation stock, C^T_{stock}, by summing the number of Internet citations, c_τ, for each of the $\hat{T}$ trade marks in a company's portfolio (Eqn. 17). This is equivalent to weighting each trade mark entering the stock with the Internet citations it induced. Note that, as we use a zero depreciation rate for trade marks, the date at which a trade mark enters the portfolio is irrelevant here.

$$C^T_{stock} = \sum_{j=1}^{\hat{T}} c_{\tau,j} \tag{17}$$

Control Variables

Finally, control variables capture different effects of companies' valuation among countries, industries, markets covered and technologies engaged in. We used the *Reuters Business Sector Scheme* as our industry classification, which distinguishes 26 different industries. This

decreases from year to year.

[10] Google is the major player in the search engine market with a market share of 58.5% in January 2008, 61.6% in April 2008 and 61.9% in July 2008.

categorisation showed a rather appropriate distribution, as none of the categories held more than 10% of all observations. Still, we grouped the six least occupied categories into one miscellaneous group.

To establish a market- and technology-oriented company profile, we segmented trade marks and patents in companies' portfolios into categories and measured the number of trade marks and patents in each category to obtain both a technology and a market profile for each company. The *market profile* of a company is a vector of 45 count variables containing the number of trade marks a company holds in each of 45 Nice classes. Similarly, the *technology profile* is a vector of count variables based on 30 technology classes defined in OECD (1994).[11] This vector represents how many patents each company holds in each of the technology areas.

These company profiles also allow to provide evidence about the representativeness of our data. First, we computed the frequencies of assigned Nice classes for both the trade marks included in the portfolios of the companies in our sample and the trademark applications in the original database of the OHIM. As shown by Table 9 in the appendix, the distribution of Nice classes covered by our sample are largely consistent with the distribution in the OHIM database.

Instruments

Some of our results rely on instrumental variables which we do not employ in our main regressions. These variables capture aspects of R&D competition as measured using patent data.

Technological Opportunity Early stages of the evolution of a technology are characterised by a large share of basic research often conducted in publicly-funded labs. In later stages of a technology, industry driven development of existing technological opportunities will dominate basic research. Then the focus is on refining existing opportunities rather than creating new ones. While there is no perfect measure for the position of a technology area in the stylised cycle of technology evolution, the share of references listed on a patent which point to non-patent literature (mostly scientific publications) can be used as a good proxy for the strength of the science link of a technology (Meyer, 2000; Narin and Noma, 1985; Narin et al., 1997; von Graevenitz et al., 2008).

Here we use the average number of non-patent references per patent in the technology areas in which a company patents as a proxy measure for the degree of new technological opportunities the company faces.

Triples We employ a measure of technological complexity suggested by von Graevenitz et al. (2008). They measure complexity of a technology area through the degree of overlap between companies' patent portfolios. Overlap leads to blocking dependencies among firms. If patents containing prior art critical to the patentability of new inventions in a field are held by two firms, each firm can block its rival's use of new patents. Then, a company can only commercialise a technology if it receives a license to use such blocking patents. In technology areas in which products draw on many patents -complex technologies- von Graevenitz et al.

[11] This classification system has been elaborated by several research institutes. These institutes include the German Fraunhofer Institute of Systems and Innovation Research (ISI), the French Patent Office (INPI), and the Observatoire des Sciences and des Techniques (OST).

(2008) document a larger number of such dependencies. In discrete technologies the inverse is shown to be true.

They measure blocking dependencies among companies by analysing the references contained in patent documents. References to older patents or to non-patent literature are included in EPO patents in order to document the extent to which inventions satisfy the criteria of patentability (Harhoff et al., 2006). Often, existing prior art limits patentability of an invention. For example, the existence of an older but similar invention can reduce the patentability of a newer invention. In these cases *critical* documents containing conflicting prior art are referenced in patent documents and are classified as X or Y references by the patent examiner at the EPO during the examination of the patent application.[12] If the patentability of a company A's inventions is frequently limited by existing patents of another company B, it is reasonable to assume that the R&D of A is blocked by B to a certain degree. If the inverse is also true, A and B are in a mutual blocking relationship which they call a blocking pair. If more than two companies own mutually blocking patents the complexity of blocking relationships increases and resolution of blocking becomes increasingly costly. To capture more complex structures of blocking they compute the number of *Triples* in which three companies mutually block each other's patents. This measure is used to describe the extent of patent thickets firms face.

5 RESULTS

Section 3 provides descriptive evidence commensurate with the complementarity of advertising and R&D investments. Here we test the hypothesis using three different approaches.

First we present results of Tobin's q regressions which allow us to establish the relative effects of investments in advertising and R&D for the market value of firms. We test for sample selection in these regressions and find evidence that companies self select into joint use of advertising and R&D, if companies use R&D.

Next we present results of regressions which explain the average level of companies' gross-profit ratio's between 2002 and 2007. To deal with endogeneity of advertising and R&D investments we instrument these using patent and trade mark measures. We also control for self selection and find additional evidence of this for R&D intensive firms.

Finally, we test the complementarity of advertising and R&D using quantile regression. The goal of this test is to determine whether there are unobserved complements to R&D and advertising which give rise to their apparent complementarity. We test whether coefficients of our regressors in the Tobin's q regression are constant across quantiles. Arias et al. (2001) employ quantile regression to identify the complementarity of unobservable ability and education. The statistical test employed is suggested by Koenker and Xiao (2002) to test for location and location-scale shifts across quantiles. Where coefficients are constant across quantiles we conclude that the complementarity of advertising and R&D is not just apparent. We also employ this test to establish the strength of the complementarity between advertising and R&D expenditures.

[12] A patent contains various different types of references – not all of them are critical. Often, related inventions which are not critical for the patentability of the invention seeking patent protection are also included in the patent document. The EPO provides a full classification of the references included in patent documents allowing us to identify critical references which are classified as X or Y.

5.1 Market Value Regressions

Here we use data on companies' market values to determine whether joint investment in advertising and R&D are valued more highly than investment in R&D or advertising by themselves. If markets are perfectly competitive, and companies' production functions exhibit constant returns to scale it has been shown (Hayashi, 1982; Hayashi and Inoue, 1991; Kataoka and Semba, 2001) that the relationship of company value V and marginal q is :

$$V_i = q_i \cdot K \ , \tag{18}$$

where K represents the production function which is homogeneous of degree one and q is marginal q and $_i$ indexes the company.

We investigate whether the production function K embodies a complementarity between R&D investments, advertising investments, patents and trade marks. To do this we assume that:

$$K = F(A_i, R_i, M_i, P_i, T_i, C_i^P, C_i^T) \ , \tag{19}$$

where A_i are physical assets, R_i is the stock of R&D investments, M_i are capitalised advertising investments, P_i is the patent stock and T_i is the stock of trade marks. All of these are the result of past and present period by period choices which companies make. Following Hall et al. (2005) the production function also includes measures of the quality of companies' research and advertising activities: C_i^P - patent citation stocks and C_i^T - trade mark citation stocks. These reflect the evaluation of companies' activities by third parties. Where these evaluations affect company value they may represent proxies of companies' success in their research and advertising activities. Hall et al. (2005) control for the quality of R&D investments using patent stocks and patent citation measures. We extend their approach by including patent stocks and trade marks stocks as well as citations to these in our regressions.

The derivation of the relationship in equation (18) does not place any restrictions on functional form of the production function, apart from the restriction of constant returns to scale. In a survey of the empirical literature Hall (1999) points to two frequently employed functional forms for the production function K. The first is additive in the arguments of the production function, the second takes the Cobb-Douglas form. We prefer the Cobb Douglas specification here for two reasons: it captures the possible complementarity of advertising and R&D well and unreported results using non linear least squares supported this functional form. The following specification is estimated:

$$\begin{aligned}\log \tfrac{V_i}{A_i} &= \log q_i + (\beta_A - 1)\log A_i \\ &+ \beta_M \log M_i + \beta_T \log T_i + \beta_{C^T} \log C_i^T + \beta_R \log R_i + \beta_P \log P_i + \beta_{C^P} \log C_i^P + \epsilon\end{aligned} \tag{20}$$

If R&D and advertising investments really are complements the following restrictions on the production function K will hold:

$$\begin{aligned}&(i)\ \frac{\partial^2 K}{\partial R_i \partial M_i} = \beta_R \beta_M \frac{V_i}{R_i M_i} > 0 \ , \quad (ii)\ \frac{\partial^2 K}{\partial P_i \partial T_i} = \beta_P \beta_T \frac{V_i}{P_i T_i} > 0 \ , \\ &(iii)\ \frac{\partial^2 K}{\partial R_i \partial T_i} = \beta_R \beta_T \frac{V_i}{R_i T_i} > 0 \ , \quad (iv)\ \frac{\partial^2 K}{\partial M_i \partial P_i} = \beta_M \beta_P \frac{V_i}{M_i P_i} > 0 \, .\end{aligned} \tag{C}$$

These restrictions are tested further below.

We control for country, technology area, market and sector effects in all regressions. Two sources of selection bias exist which might distort our results: (i) not all companies report advertising and/or R&D investments, (ii) we did not identify patent or trade mark stocks for all firms. For instance we use only European patents and Community Trade Marks to consolidate IP portfolios. However, companies may still hold patents or trade marks at the national level which we do not observe. It should also be noted that companies in many countries can choose whether to disclose advertising or R&D in their income statement or not (Hall and Oriani, 2006).

We deal with these potential sources of selection bias by distinguishing between companies whose advertising efforts are at least partly observed, companies whose R&D efforts are at least partly observed and those for which we observe advertising and R&D jointly. Then self selection may arise in the decision by an R&D intensive company to also invest significantly in advertising and vice versa. Here, we interpret the absence of reporting on advertising and absence of trade mark registrations as evidence that advertising is not very important for the company relative to R&D for which we observe at least either patent registrations or R&D expenditure. Absence of information on R&D investments is treated in an analogous way. Therefore the sample contains companies that make joint use of advertising and R&D and others that use only advertising or only R&D. Below we investigate whether there is self selection into joint use of advertising and R&D which gives rise to a sample selection bias.

We are not the first to include advertising and R&D in a market value regression (Hall, 1993; Greenhalgh and Rogers, 2006; Sandner, 2008). These studies confirm that advertising is a significant determinant of market value. Here, we extend the framework proposed by Hall et al. (2005) to include measures of the quality of advertising investments. To do this the level of citations to trade marks on the Internet is measured using Google's search engine. Toivanen et al. (2002) and Hall and Oriani (2006) control for the endogeneity of advertising or R&D measures in market value regressions. However, we are the first to control for the endogeneity of joint use of advertising and R&D in order to establish whether companies self select into using both types of investments.

Table 4 shows how measures of advertising investments, companies' trade mark stocks and citations to trade marks affect the significance and level of coefficients for R&D and patent stocks and citations. The table contains four different specifications. The first excludes advertising and trade marks from the regression entirely. Next we include advertising expenditure, trade mark stocks and Google citations in the regressions one after the other.

Table 4 shows that all factors included in the production function enter with a positive coefficient or are not significantly different from zero. In particular the coefficients for the patent and trade mark stocks are not significant. Unreported regressions show this to be the result of inclusion of citations to patents and trade marks. Hall et al. (2007) find that patent citations are not significant if included jointly with patent stocks in regressions very similar to our base regression in Table 4. These findings suggest that patent stocks and citation stocks are often highly correlated, at least when it comes to patents issued by the EPO.

A test for constant returns to scale shows that the hypothesis cannot be rejected. We test the null hypothesis that the sum of the exponents for the elements of the production function is equal to one. Given the functional form we estimate this implies that the coefficient on assets has the same magnitude but opposite sign as the sum of coefficients on R&D, patent, advertising and trade mark variables. The test statistic and corresponding p value are reported in Table 4. We also test for the complementarity of advertising and R&D efforts as discussed

Table 4: Market Value Regressions

Variables	(1) Base	(2) Advertising	(3) Trade Marks	(4) Google
log (R&D Investment Stock)	0.014***	0.013***	0.013***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
log (Patent Stock)	-0.008	-0.006	-0.005	-0.006
	(0.016)	(0.016)	(0.016)	(0.016)
log (Patent Citations Stock)	0.026	0.024	0.023	0.023
	(0.015)	(0.015)	(0.015)	(0.015)
log (Advertising Stock)		0.008**	0.008**	0.008*
		(0.003)	(0.003)	(0.003)
log (Trade Mark Stock)			0.003	0.002
			(0.010)	(0.010)
log (Google Citations)				0.006*
				(0.002)
log (Asset Stock)	-0.029***	-0.031***	-0.031***	-0.032***
	(0.006)	(0.006)	(0.006)	(0.006)
Joint Investment Dummy (D_B)	-0.001	-0.008	-0.010	-0.007
	(0.017)	(0.017)	(0.018)	(0.018)
Japan	-0.327***	-0.327***	-0.326***	-0.326***
	(0.018)	(0.017)	(0.018)	(0.018)
UK	-0.054	-0.041	-0.041	-0.042
	(0.028)	(0.028)	(0.028)	(0.028)
China	0.267**	0.275**	0.276**	0.275**
	(0.100)	(0.100)	(0.100)	(0.100)
Canada	-0.046	-0.035	-0.034	-0.036
	(0.044)	(0.044)	(0.044)	(0.044)
Taiwan	-0.174***	-0.159***	-0.159***	-0.161***
	(0.046)	(0.046)	(0.046)	(0.046)
Germany	-0.219***	-0.214***	-0.214***	-0.213***
	(0.037)	(0.037)	(0.037)	(0.037)
Australia	0.114*	0.119*	0.119*	0.118*
	(0.047)	(0.047)	(0.047)	(0.047)
France	-0.113**	-0.102*	-0.102*	-0.100*
	(0.041)	(0.041)	(0.041)	(0.041)
Hong Kong	-0.007	0.009	0.010	0.013
	(0.090)	(0.090)	(0.090)	(0.090)
Technology Area Dummies	YES	YES	YES	YES
Nice Class Dummies	YES	YES	YES	YES
Business Sector Dummies	YES	YES	YES	YES
Seniorities Dummy	0.031*	0.029	0.026	-0.049
	(0.016)	(0.016)	(0.018)	(0.036)
Constant	0.968***	0.982***	0.981***	0.983***
	(0.051)	(0.052)	(0.052)	(0.052)
R-squared	0.275	0.277	0.277	0.279
Constant Returns to Scale (F-Test)	0.37			2.03
Constant Returns to Scale (p-value)	0.543			0.154
N	2093	2093	2093	2093

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Standard errors in parentheses

above (C). The tests are partly based on the regressions reported in Table 6 below. Wald tests of the hypothesis that the product of two coefficients is zero are reported in Table 5. This shows that only the complementarity of advertising and R&D expenditures is confirmed by these tests. The findings are not surprising given the non significant coefficients on patent and trade mark stocks.

It is possible to interpret measures of patent and trade mark citations as proxy measures of R&D and advertising strategies which are focused on quality rather than as measures capturing luck in R&D and advertising. Then additional tests of complementarities of advertising and patent citations and R&D and trade mark citations are meaningful. These provide some additional evidence in favour of complementarities. Notice that these tests suggest highly cited trade marks are a complement to R&D investments whilst highly cited patents are not a complement to advertising investments.

Table 5: Wald Tests of Complementarity

		Hypothesis tested					
		$\beta_R * \beta_M = 0$	$\beta_R * \beta_T = 0$	$\beta_P * \beta_T = 0$	$\beta_P * \beta_M$=0	$\beta_R * \beta_{C^T}$=0	$\beta_M * \beta_{C^P}$=0
Full sample	F-Statistic	4.88	0.09	0.06	0.14	4.62	1.89
	p-Value	**0.027**	0.768	0.803	0.707	**0.032**	0.17
Advertising sample	F-Statistic	5.94	0.87	0.18	0.22	4.45	1.84
	p-Value	**0.015**	0.35	0.675	0.642	**0.035**	0.177
R&D sample*	F-Statistic	4.06	0.11	0.11	1.67	3.81	1.8
	p-Value	**0.044**	0.738	0.745	0.196	**0.051**	0.179

*Here we test the sample selection model.

Table 6 below provides regressions in which we test the endogeneity of the joint investment dummy D_B using sample selection models. We estimate Roy models (Roy, 1951) in which the joint investment dummy is treated as endogenous. The choice to jointly invest in advertising and R&D is modeled using information on companies' patenting and trade marking strategies. We estimate three models: a pooled model and two models on overlapping subsamples. The first of these covers all companies for which we observe information on advertising, the second covers all companies for which we observe information on R&D.

In each case there is at least one variable which identifies the selection equation and which is significant as Table 6 shows. In the case of the R&D subsample, which is most interesting, these comprise the average level of technological opportunity a company faced in the year 2000 (*NPR 2000*), the extent of patent thickets a company faced in that year (*Triples 2000*) and the number of critical references a company received on its patent stock (*Crit. Pat. Stock* Y). These variables capture variation in the type of technological competition which companies face. It is interesting to note that companies facing higher technological opportunity, as measured by non patent references (*NPR* 2000), and companies facing greater patent thickets (*Triples* 2000) were more likely to also employ advertising and trade marks.

There is evidence for self selection into joint investment in advertising and R&D only in the subsample of companies which undertake R&D. Here the choice to invest in advertising along with R&D raises companies' market value by 18.7%. We cannot reject the hypothesis that this decision is affected by unobserved heterogeneity as the significant correlation coefficient (ρ)

for the error terms indicates.

Table 6: Market Value Regressions with Endogenous Company Types

	Full	Full Outcome	Selection	Adv.	Adv. Outcome	Adv. Selection	R&D	R&D Outcome	R&D Selection
Dependent Variable	$\log(\boldsymbol{Q})$	$\log(\boldsymbol{Q})$	$\boldsymbol{D}_B$	$\log(\boldsymbol{Q})$	$\log(\boldsymbol{Q})$	$\boldsymbol{D}_B$	$\log(\boldsymbol{Q})$	$\log(\boldsymbol{Q})$	$\boldsymbol{D}_B$
log (R&D Stock)	0.013***	0.013***		0.015***	0.015***		0.011***	0.010***	
	(0.003)	(0.003)		(0.003)	(0.003)		(0.003)	(0.003)	
log (Patent Stock)	-0.006	-0.005		-0.009	-0.007		-0.014	-0.017	-0.401***
	(0.016)	(0.016)		(0.019)	(0.019)		(0.017)	(0.016)	(0.103)
log (Pat. Cit. Stock)	0.024	0.025	0.561***	0.028	0.027		0.030†	0.025†	
	(0.015)	(0.015)	(0.114)	(0.018)	(0.018)		(0.015)	(0.015)	
log (Adv. Stock)	0.008*	0.007*		0.009**	0.009**		0.008*	0.008*	
	(0.003)	(0.003)		(0.003)	(0.003)		(0.003)	(0.003)	
log (TM Stock)	0.003	0.004	0.943***	0.010	0.010		0.005	0.001	
	(0.010)	(0.010)	(0.093)	(0.011)	(0.011)		(0.012)	(0.011)	
log (Google Cit.)	0.006*	0.006*	-0.019†	0.006*	0.006*		0.006*	0.006*	
	(0.002)	(0.002)	(0.010)	(0.002)	(0.002)		(0.003)	(0.003)	
log (Assets)	-0.031***	-0.031***		-0.040***	-0.040***		-0.022**	-0.021**	
	(0.006)	(0.006)		(0.007)	(0.007)		(0.008)	(0.007)	
Jnt. Inv.D $[\boldsymbol{D}_B]$	-0.008	-0.016		-0.003	-0.008		-0.016	0.187***	
	(0.018)	(0.028)		(0.023)	(0.026)		(0.026)	(0.049)	
Seniorities D	-0.049	-0.049		-0.050	-0.050		-0.072†	-0.071†	
	(0.036)	(0.035)		(0.036)	(0.035)		(0.042)	(0.040)	
Product Market HHI			1.896***			0.857*			
			(0.181)			(0.340)			
Technology HHI			2.722***						
			(0.183)						
log NPR 2000			-0.795**			476.133***			0.719**
			(0.278)			(139.249)			(0.220)
log Triples 2000			0.419***			-4.157			0.224***
			(0.076)			(2.812)			(0.068)
log Pat. Cit. Stock Y			-0.619***						-0.257*
			(0.170)						(0.109)
Country D	YES	YES	YES	YES	YES	YES	YES	YES	YES
Technology D	YES	YES	YES	YES	YES	NO	YES	YES	YES
Market D	YES	YES	YES	YES	YES	YES	YES	YES	NO
Sector D	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.978***	0.981***	-2.975***	1.062***	1.064***	-2.035***	0.920***	0.766***	1.272***
	(0.052)	(0.051)	(0.203)	(0.057)	(0.055)	(0.360)	(0.065)	(0.072)	(0.190)
ρ		.0287			.0400			-.4414	
p-Value for ρ		.7056			.7181			.0002	
R-squared	0.278			0.251			0.322		
$-$ logL		907			441			746	
CRS (F or χ^2)	2.03	2.20		2.37	2.62		3.02	0.86	
CRS p-Value	0.15	0.14		0.12	0.11		0.08	0.36	
N	2093	2093		1801	1801		1565	1565	

*** p<0.001, ** p<0.01, * p<0.05, † p<0.1
Standard errors in parentheses

The increase in market value brought about by the decision to invest heavily in advertising is astonishingly large. How can companies which do not adopt this strategy survive? The negative sign of the correlation coefficient may offer a clue: this suggests that companies which are affected by unobserved shocks making them more prone to adopt advertising tend to experience unobserved shocks reducing their market value. Overall adopting a strategy of combining advertising with R&D seems to be associated with costs which we cannot as yet identify.

Overall this section provides some evidence of complementarities between advertising and R&D for companies which rely primarily on R&D investments for competitive advantage. In contrast there is no evidence that companies which rely primarily on advertising benefit greatly from additional R&D expenditures.

5.2 Profit Ratio Regressions

Next we provide regressions in which the dependent variable is a five year average of companies' gross profit margins. We seek to determine whether joint investments in advertising and R&D raise profits relative to sales faster than just the use of advertising or R&D alone. Our most important right hand side variables are therefore measures of R&D and advertising intensity and a dummy capturing the joint use of advertising and R&D. We run two separate regressions comparing first companies that only use R&D to those that rely on R&D and advertising and second companies that only use advertising to those that use both R&D and advertising.

Regressions of the kind we estimate here are generally viewed as suspect, since it is highly likely that the explanatory variables are endogenous. Schmalensee (1989) argues that the endogeneity arising from simultaneity bias is hard to purge in cross section regressions which aim to identify long run equilibrium relationships between profit measures and measures of investment. The challenge is to identify valid instruments that are not themselves endogenous in the long run. Clearly the R&D to sales and advertising to sales ratios are candidates for endogeneity, especially given the nature of the dependent variable here. Additionally, our results in the previous section suggest that the dummy variable capturing the joint use of advertising and R&D captures self selection and is also endogenous.

In spite of these challenges we present results from the regressions because we believe we have found valid instruments and because our findings from the regressions reported are consistent with those from market value regressions reported in the previous section. We find strong evidence for simultaneity bias and for self selection in one case, conditional on the validity of our instruments. Since we have more instruments than endogenous variables we test the validity of our instruments and find them to be valid.

Table 7 sets out the results from three different regressions for each one of the two subsamples of our data. First we estimate regressions in which we do not instrument the endogenous variables. These are presented as a basis for comparison. The table also contains estimates from two regressions respectively for each subsample in which we instrument the advertising to sales and R&D to sales ratios as well as the dummy variable indicating joint advertising and R&D. The first of these regressions uses two step GMM, the second uses the continuously updated GMM estimator (CUE) introduced by Hansen et al. (1996). Hahn et al. (2004) argue that this estimator is less prone to weak instruments problems than GMM. Reported standard errors are heteroscedasticity robust. Estimation was performed using IVREG2 in Stata (Baum et al., 2002).

Table 7 shows that higher R&D to sales and advertising to sales ratio's both increase gross-profits relative to sales. This is true in both subsamples, although the advertising to sales ratio is only weakly significant in the subsample of R&D performing firms. The results indicate that there is some downward bias of the absolute size of these effects if endogeneity is ignored.

The sign of the bias is consistent with standard derivations of the effects of simultaneity bias if the gross-profit ratio has a positive effect on the advertising to sales and R&D to sales ratio's as we would expect.

The results of the two step GMM and continuously updated GMM estimators are quite similar. More interestingly, the results indicate that the Joint Investment Dummy is significant only in the R&D subsample. Although it is only weakly significant, the effect is clearly stronger than in the advertising subsample. This finding is consistent with the results we obtain from the Tobin's q regressions reported in the previous section.

Table 7: Gross-Profit-Ratio Regressions

	Adv.	Adv. GMM	Adv. CUE	R&D	R&D GMM	R&D CUE
R&D/ Sales	25.191***	34.791***	34.971***	23.096***	28.557***	28.808***
	(1.966)	(9.725)	(9.719)	(1.895)	(7.433)	(7.472)
Adv. / Sales	28.215***	50.138**	50.987**	29.265***	39.833†	40.764†
	(2.658)	(17.682)	(17.625)	(3.110)	(20.668)	(21.009)
Jnt. Inv. Dummy	-0.215	-1.246	-1.284	2.972**	3.938†	3.900†
	(1.318)	(2.742)	(2.742)	(1.033)	(2.027)	(2.035)
Technology Dummies	YES	YES	YES	YES	YES	YES
Business Sector Dummies	YES	YES	YES	YES	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES
Constant	25.785***	25.078***	25.057***	22.328***	20.563***	20.550***
	(1.969)	(2.212)	(2.211)	(1.979)	(2.544)	(2.552)
Adjusted R-squared	0.363	0.337	0.335	0.468	0.460	0.459
Hansen J Statistic		1.415	1.416		2.952	2.931
p- value		0.702	0.702		0.399	0.402
Weak Identification Test		2.982	2.982		2.614	2.614
Under Identification Test		16.638	16.638		15.259	15.259
p-value		0.002	0.002		0.004	0.004
N	1611	1611	1611	1410	1410	1410

*** $p<0.001$, ** $p<0.01$, * $p<0.05$ † $p<0.1$

Standard errors in parentheses

Instruments used: log Patent Stock,log Trade Mark Stock, log Patent Citations Stock, log Google Citations 2008, log Trade Mark Oppositions Brought, log Trade Mark Oppositions Received.

Our instruments for R&D and advertising are derived from trade mark and patent data. They are patent and trade mark stocks (log Patent Stock, log TM Stock), citations to companies' lagged patent and trade mark stocks (log Patent Citations Stock , log Google Citations) and measures of opposition activity related to the trade mark stock (log TM oppositions brought , log TM oppositions received). These variables are correlated with the value of companies' lagged patent and trade mark stocks (Trajtenberg, 1990; Lanjouw and Schankerman, 2004; Hall et al., 2005; Sandner, 2008; von Graevenitz, 2007). In the case of patents, citations are based on the work of patent examiners at the Europe-an patent office. Citations included refer to patents with priority date until 2002. Trade mark citations were collected from Google in 2008. We include only citations to trade marks that were applied for with seniorities before 2004. This implies that the Google citations are to trade marks which have existed since before 1996. The importance of such trade marks is less likely to be the result of factors determining the average gross profit ratio for the period after 2002. Finally, the level of trade mark oppositions received and brought is based on the stock of trade mark applications at OHIM between 1996 and 2004. As such the period on which these variables are based overlaps partly with the sample period for the gross-profit ratio.

Since we have more than three instruments we test the validity of our instrument sets using the Hansen test. Table 7 shows that we cannot reject the null hypothesis, that the instruments are uncorrelated with the error term of our regression. We also investigate whether the instruments are underidentified. This is a test whether the instruments are correlated with the endogenous variables. In this case we can reject the null hypothesis of underidentification at the 1% level in all regressions reported in Table 7. Finally we also report the test statistic for weak identification in the table. This indicates that the instruments are not very strong, however the statistic is hard to interpret in this case as we use an estimator which is robust to heteroscedasticity (Baum et al., 2002). The fact that the continuously updated GMM results are so similar to those obtained from two step GMM suggest to us that our results are not affected strongly by a weak instruments bias.

Overall these results confirm what we have found in the previous section: advertising seems to complement R&D for companies that rely primarily on R&D to achieve competitive advantage. In contrast there is no evidence that R&D is a complement to advertising. Just as in the previous section we find that at the margin advertising and R&D have statistically indistinguishable effects on gross-profits.

5.3 A Quantile Regression Test for Complementarity

While the results in the previous section fail to reject the hypothesis that R&D investment, advertising expenditure, patent stocks and trade mark stocks are complements the test we use has a weakness. We are unable to exclude the possibility that the apparent complementarity of R&D investment and advertising within the production function is a consequence of unobserved heterogeneity (Athey and Stern, 1998; Miravete and Pernias, 2006). This section sets out a more stringent test for a complementarity between observable determinants of an outcome and unobservable heterogeneity as discussed by Arias et al. (2001). They suggest using quantile regression to test for such a complementarity.

Complementarity between two strategic choice variables exists, if an increase in one choice raises the marginal return to the other (Topkis, 1978; Vives, 1990; Milgrom and Roberts, 1990). The results of the previous section suggest that companies' investments in R&D and advertising as well as the level of patent and trade mark applications made by these companies are complements in this sense. Various tests of complementarity of two observed explanatory variables have been developed in the literature (Arora and Gambardella, 1990; Arora, 1996). Arora (1996) and Athey and Stern (1998) argue that evidence of complementarities not derived from a structural model could be due to unobserved heterogeneity just as well as true complementarity of observed variables. One way of dealing with this problem is to develop a structural model which allows to separate influences of unobserved heterogeneity and of the true complementarity (Athey and Stern, 1998; Miravete and Pernias, 2006).

Structural models generally involve restrictive assumptions, for instance on the distribution of errors. Therefore, Arias et al. (2001) use quantile regression to investigate the complementarity of education and ability. Quantile regression imposes fewer restrictions on the distribution of errors. Following Arias et al. (2001) we use quantile regression to exclude the possibility that unobserved determinants of companies' market value are the reason for the apparent complementarity of advertising and R&D in our sample. If such complements existed, then the returns to advertising or R&D should differ across the conditional distribution

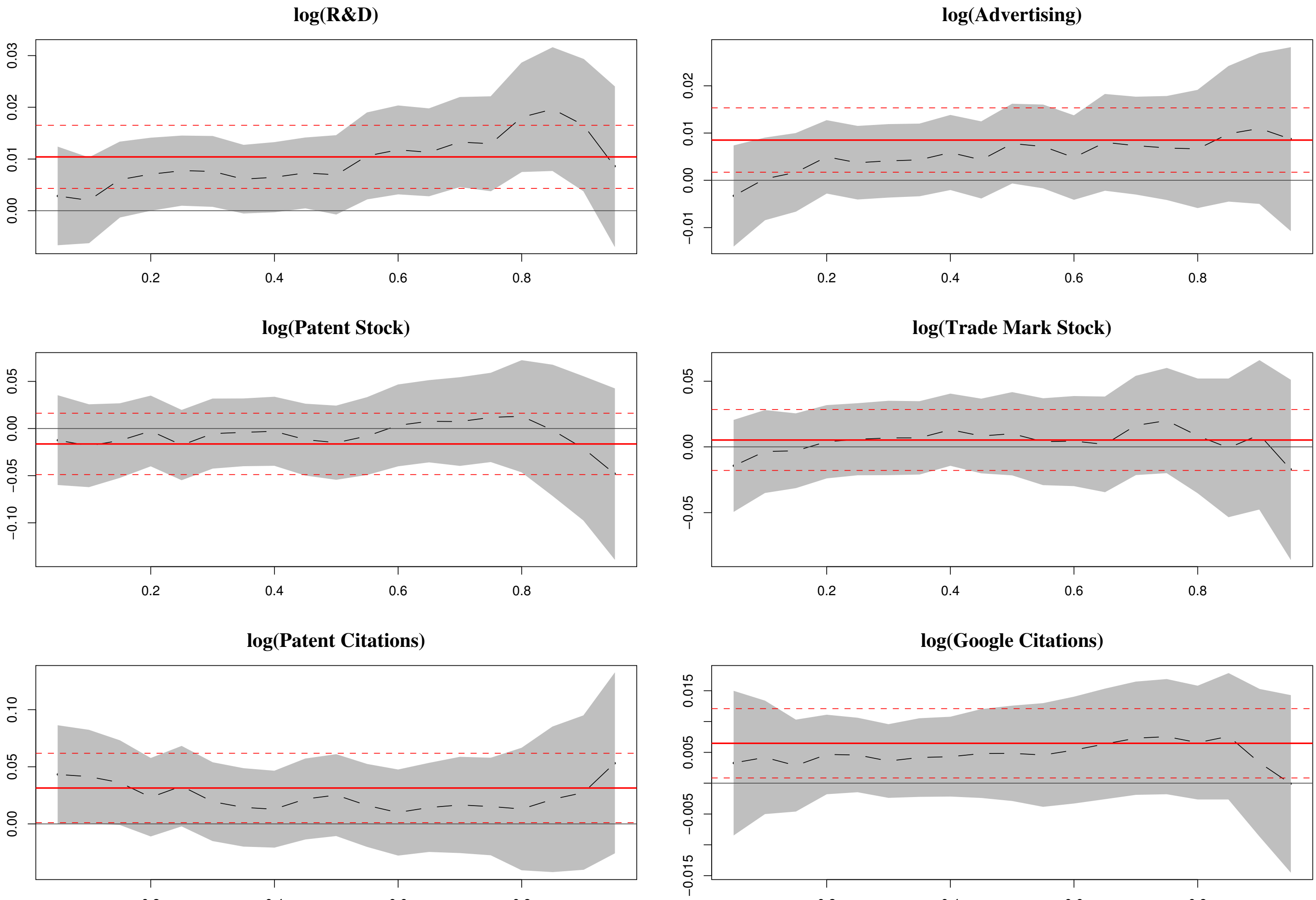

Figure 4: Selected parameter estimates from a Tobin's q regression using quantile regression. Black line represents the quantile regression estimates, with the grey area representing their 95% confidence interval. This was calculated using bootstrap with 1200 repetitions. The solid red line represents the OLS estimate, the dashed red line the 95% confidence interval of those estimates. These regressions were performed on the subsample of companies for which we observe evidence of R&D investments ($N = 1565$). Note: Estimation performed using the package quantreg (Koenker, 2008) in R (R Development Core Team, 2008).

of companies' market values. We estimate quantile treatment effects of advertising and R&D on market value and test whether these treatment effects are constant across the quantiles of market value (Koenker and Hallock, 2001; Koenker, 2005). To do this we employ the location shift test developed by Koenker and Xiao (2002). The null hypothesis for the test is that the quantile regression slopes are constant. The alternative hypothesis is that of a general quantile regression alternative. Arias et al. (2001) show that an omitted variable which is a complement to an observed variable shows up in the quantile regression slopes of the observed variable. In the case of complements these quantile regression slopes will be increasing as the marginal effects estimated at different quantiles capture the effect of the omitted variable. If this effect is significant the null hypothesis of the location shift test is rejected.

We employ this test in two stages. First we estimate the Tobin's q regressions discussed in Section 5.1 by quantile regression to determine whether there are further unobserved complements to advertising and R&D missing from the specification. We do this for the whole sample as well as the two sub samples. Additionally, we also estimate each specification omitting either the advertising or the R&D related variables to determine whether the test provides evidence of a significant complementarity between advertising and R&D.

Figure 5.3 presents the quantile regression estimates of the six variables which capture effects of R&D and advertising related intangible assets in the production function. The marginal effects for each variable are plotted from the 0.05^{th} to the 0.95^{th} percentile in increments of 0.05. Each panel also provides the 95% confidence bounds for the marginal effects as a grey band. Furthermore we include the marginal effects from OLS (solid thick red line) along with its confidence bands (dashed red line). The results presented here are for the sub-sample of companies which undertake R&D. We include the inverse mills ratio as a regressor to control for sample selection.[13]

Examination of Figure 5.3 reveals that there is almost no evidence for any significant differences between the marginal effects from quantile regression and those from our OLS results reported in Section 5.1 above. This indicates that there is no unobserved heterogeneity which is a complement or substitute to the factors of the production function which are contained in our main specification.

Table 8: Khmaladze Location Shift Tests

	Full sample			Advertising int.			R&D int		
		No adv	no R&D		No R&D	No adv		No adv	No R&D
Explanatory Variables	20	17	17	20	17	17	20	17	17
Trim	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Critical Value 1%	20.14	17.59	17.59	20.14	17.59	17.59	20.14	17.59	17.59
Critical Value 5%	18.3	15.95	15.95	18.3	15.95	15.95	18.3	15.95	15.95
Test Statistic	15.37	11.88	**18.55**	14.15	**18.76**	13.91	12.72	11.39	12.93
Explanatory Variables	20	17	17	20	17	17	20	17	17
Trim	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Critical Value 1%	22.02	19.24	19.24	22.02	19.24	19.24	22.02	19.24	19.24
Critical Value 5%	20.11	17.44	17.44	20.11	17.44	17.44	20.11	17.44	17.44
Test Statistic	18.75	11.86	**20.43**	14.13	**20.34**	13.78	14.55	11.24	**18.12**
N	2093	2093	2093	1801	1801	1801	1565	1565	1565

To provide a more formal test we present results of applying the Khmaladze location shift test suggested by Koenker and Xiao (2002); Koenker (2005). This is a joint test of the hypothesis that all estimated treatment effects are constant. Table 8 sets out results from two sets of tests. As above we apply the test to the full sample as well as the two sub samples. We investigate whether we can reject the null hypothesis in each sample. Additionally, we drop the advertising and the R&D related variables from the specification to see whether the test suggests that there is a significant complementarity.

Table 8 provides information on the number of regressors we employed, the range over which we applied the test (Trim), the critical values for the test as reported by Koenker and

[13] We are currently working to apply the semiparametric approach to sample selection in the context of quantile regression suggested by Buchinsky (2001) to our problem. At present the bootstrapped standard errors reported in Figure 5.3 do not take into account the implicit two stage nature of our estimator.

Xiao (2002) in their electronic appendix and the test statistic we obtain.

The results of these tests are remarkably consistent across all samples we investigate. We find no evidence of omitted complements or substitutes to the variables included in the specifications we estimate. In other words we are unable to reject the null hypothesis of a pure location shift. However, as soon as we omit the variables capturing R&D investment we are able to reject the pure location shift hypothesis. This is not the case when we omit variables capturing advertising investment. These findings indicate that advertising and R&D investments are complements to one another.

6 CONCLUSION

In this paper we investigate a simple question: is advertising a complement to R&D? The answer to the question turns out to be more complicated than might be expected: we find that companies which undertake R&D benefit from complementary investments in advertising. Companies' market values and gross-profit ratios are significantly higher if the combine advertising with R&D than those of companies which rely solely on R&D. In contrast, companies in advertising intensive industries are not valued more highly if they also undertake R&D, nor do they earn higher profits.

This result is established using forward and backward looking measures of companies' success: market value and the gross-profits ratio. We show that in the set of companies which rely on R&D some complement their R&D investments with advertising investment. These companies have significantly higher market values than companies which do not employ advertising as intensively. Companies self select into complementing R&D with advertising. There is also some evidence of unobservable costs of this strategy which may explain why not all companies complement R&D with advertising to the same extent.

The set of companies which rely on advertising also contains some which undertake R&D investments. Here, the decision to invest in R&D is due to observable industry characteristics. There is no evidence for any difference in market values or profits between companies that complement advertising with R&D and those that do not.

Finally, we investigate whether the complementarity of R&D and advertising is apparent or real. An apparent complementarity could be the consequence of an unobserved complement to advertising and R&D. Drawing on Arias et al. (2001) and Koenker and Xiao (2002) we investigate this possibility using quantile regression. We find no confirmation for the existence of unobserved complements and conclude that the complementarity we have found is real.

Our finding may be significant in several respects. First it shows that any analysis of market power in R&D intensive industries which neglects effects of advertising is likely to be incomplete. This point is most obviously true for the case of competition between pharmaceutical companies which are often criticised for high levels of marketing outlays. However the point may apply more generally to the analysis of effects of the patent system. Our analysis above shows that R&D intensive firms which face patent thickets are more likely to invest in advertising. This suggests that perturbations in the effectiveness of one escalation mechanism seem to lead to substitution of investments towards another. Thus the interaction between advertising and R&D for R&D intensive industries would seem to merit further study.

Secondly, our result is interesting for those who would like to employ data on trade marks and on advertising as proxy measures for R&D activities. It shows that this approach has considerable merit for R&D intensive industries. In contrast, conventional forms of innovation are not complementary to advertising in advertising intensive industries. Whether the trade mark register hides information on innovation in service and retail industries remains an open question.

Finally, our results may have some bearing on the endogenous sunk costs literature. Sutton (1998) distinguishes between technologies in which R&D results apply over a wide range of applications and those where they are limited to specific technological trajectories. It seems likely that advertising has a greater role to play where the effects of R&D investment are weakened by strong segmentation of technologies into different trajectories. This remains a question for future work however.

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A Additional Information On Data

Table 9: Frequencies of assigned Nice classes

		Sample		Total (only sen.)		Total	
#	**Name of Nice class**	**#**	**%**	**#**	**%**	**#**	**%**
1	Chemicals	989	6.2%	3253	3.2%	21029	2.0%
2	Paints, varnishes and lacquers	313	2.0%	1174	1.1%	7103	0.7%
3	Substances for laundry use	666	4.2%	3845	3.7%	32160	3.0%
4	Industrial oils and greases	401	2.5%	979	1.0%	5697	0.5%
5	Pharmaceutical and sanitary preparations	1021	6.4%	4256	4.1%	37508	3.5%
6	Common metals	292	1.8%	2265	2.2%	17856	1.7%
7	Machines and machine tools	522	3.3%	3202	3.1%	25567	2.4%
8	Hand tools and implements	148	0.9%	1223	1.2%	8693	0.8%
9	Scientific apparatus	1296	8.1%	8531	8.3%	120080	11.3%
10	Medical apparatus	290	1.8%	1636	1.6%	19396	1.8%
11	Lighting and heating	400	2.5%	2663	2.6%	21326	2.0%
12	Vehicles	640	4.0%	2079	2.0%	18636	1.8%
13	Firarms	44	0.3%	174	0.2%	1324	0.1%
14	Precious metals and jewellery	218	1.4%	1583	1.5%	13757	1.3%
15	Musical instruments	53	0.3%	249	0.2%	1990	0.2%
16	Paper, packaging and printing	889	5.5%	5750	5.6%	67784	6.4%
17	Rubber and gum	360	2.2%	1710	1.7%	11158	1.0%
18	Leather	279	1.7%	2601	2.5%	23348	2.2%
19	Building materials (non-metallic)	237	1.5%	1736	1.7%	12732	1.2%
20	Furniture	226	1.4%	2188	2.1%	18348	1.7%
21	Household or kitchen utensils	276	1.7%	1935	1.9%	16760	1.6%
22	Ropes, sails and bags	91	0.6%	525	0.5%	3673	0.3%
23	Yarns and threads for textile use	49	0.3%	250	0.2%	1873	0.2%
24	Textiles and textile goods	177	1.1%	1658	1.6%	13434	1.3%
25	Clothing, footwear	578	3.6%	5361	5.2%	49138	4.6%
26	Lace, pins and needles	68	0.4%	494	0.5%	3910	0.4%
27	Materials for covering floors	81	0.5%	578	0.6%	4469	0.4%
28	Games, playthings and decorations	352	2.2%	2252	2.2%	28182	2.6%
29	Meat, fish and vegetables	368	2.3%	3066	3.0%	23215	2.2%
30	Coffee, bread and salt	444	2.8%	3327	3.2%	26784	2.5%
31	Agricultural and forestry products	166	1.0%	1640	1.6%	12250	1.2%
32	Beers	327	2.0%	2060	2.0%	17138	1.6%
33	Alcoholic beverages	195	1.2%	2265	2.2%	17737	1.7%
34	Tobacco, matches	140	0.9%	638	0.6%	4569	0.4%
35	Advertising, business management	487	3.0%	4700	4.6%	68505	6.4%
36	Insurance and financial affairs	319	2.0%	1967	1.9%	31077	2.9%
37	Building construction	450	2.8%	2452	2.4%	24668	2.3%
38	Telecommunications	381	2.4%	2416	2.4%	41600	3.9%
39	Transport	329	2.1%	2382	2.3%	24439	2.3%
40	Treatment of materials	138	0.9%	858	0.8%	9568	0.9%
41	Education, sport and culture	408	2.5%	3651	3.6%	53009	5.0%
42	Scientific, technological and research services	856	5.3%	6245	6.1%	88170	8.3%
43	Services for providing food and drink	33	0.2%	377	0.4%	6858	0.6%
44	Medical services	26	0.2%	296	0.3%	5703	0.5%
45	Personal and social services	4	0.0%	71	0.1%	1884	0.2%

B Mathematical Appendix

$$\mathcal{L}(v, w, \lambda) = F(v, w) - \lambda(S\pi - \epsilon v^{\varrho} - \gamma w^{\mu}) \tag{21}$$

The Hessian for the constrained optimization problem set out in Section 2 above is:

$$\begin{bmatrix} \frac{\partial^2 \mathcal{L}}{\partial v^2} & \frac{\partial^2 \mathcal{L}}{\partial v \partial w} & \frac{\partial^2 \mathcal{L}}{\partial v \partial \lambda} \\ \frac{\partial^2 \mathcal{L}}{\partial w \partial v} & \frac{\partial^2 \mathcal{L}}{\partial w^2} & \frac{\partial^2 \mathcal{L}}{\partial w \partial \lambda} \\ \frac{\partial^2 \mathcal{L}}{\partial \lambda \partial v} & \frac{\partial^2 \mathcal{L}}{\partial \lambda \partial w} & \frac{\partial^2 \mathcal{L}}{\partial \lambda^2} \end{bmatrix} \tag{22}$$

This matrix is negative definite if we can show that the diagonal elements of the following transformed matrix are negative (Pemberton and Rau, 2001):

$$\begin{bmatrix} \frac{\partial^2 \mathcal{L}}{\partial v^2} & \frac{\partial^2 \mathcal{L}}{\partial v \partial w} & \frac{\partial^2 \mathcal{L}}{\partial v \partial \lambda} \\ 0 & \frac{\partial^2 \mathcal{L}}{\partial w^2} - \frac{\partial^2 \mathcal{L}}{\partial v \partial w} \frac{\frac{\partial^2 \mathcal{L}}{\partial w \partial v}}{\frac{\partial^2 \mathcal{L}}{\partial v^2}} & \frac{\partial^2 \mathcal{L}}{\partial w \partial \lambda} - \frac{\partial^2 \mathcal{L}}{\partial v \partial \lambda} \frac{\frac{\partial^2 \mathcal{L}}{\partial w \partial v}}{\frac{\partial^2 \mathcal{L}}{\partial v^2}} \\ 0 & 0 & \left(\frac{\partial^2 \mathcal{L}}{\partial \lambda^2} - \frac{\partial^2 \mathcal{L}}{\partial v \partial \lambda} \frac{\frac{\partial^2 \mathcal{L}}{\partial w \partial v}}{\frac{\partial^2 \mathcal{L}}{\partial \lambda \partial v}} \right) - \left(\frac{\partial^2 \mathcal{L}}{\partial w \partial \lambda} - \frac{\partial^2 \mathcal{L}}{\partial v \partial \lambda} \frac{\frac{\partial^2 \mathcal{L}}{\partial w \partial v}}{\frac{\partial^2 \mathcal{L}}{\partial v^2}} \right) \frac{\left[\frac{\partial^2 \mathcal{L}}{\partial \lambda \partial w} - \frac{\partial^2 \mathcal{L}}{\partial v \partial w} \frac{\frac{\partial^2 \mathcal{L}}{\partial w \partial v}}{\frac{\partial^2 \mathcal{L}}{\partial \lambda \partial v}} \right]}{\left(\frac{\partial^2 \mathcal{L}}{\partial w^2} - \frac{\partial^2 \mathcal{L}}{\partial v \partial w} \frac{\frac{\partial^2 \mathcal{L}}{\partial w \partial v}}{\frac{\partial^2 \mathcal{L}}{\partial v^2}} \right)} \end{bmatrix} \tag{23}$$

where

$$\frac{\partial^2 \mathcal{L}}{\partial v^2} = \frac{\partial^2 F}{\partial v^2} - \lambda S \frac{\partial^2 \pi}{\partial v^2} + \epsilon \varrho(\varrho - 1) v^{\varrho - 2} \tag{24}$$

$$\frac{\partial^2 \mathcal{L}}{\partial w^2} = \frac{\partial^2 F}{\partial w^2} - \lambda S \frac{\partial^2 \pi}{\partial w^2} + \epsilon \mu(\mu - 1) w^{\mu - 2} \tag{25}$$

$$\frac{\partial^2 \mathcal{L}}{\partial \lambda^2} = 0 \tag{26}$$

$$\frac{\partial^2 \mathcal{L}}{\partial v \partial w} = \frac{\partial^2 F}{\partial v \partial w} - \lambda S \frac{\partial^2 \pi}{\partial v \partial w} \tag{27}$$

$$\frac{\partial^2 \mathcal{L}}{\partial v \partial \lambda} = \frac{\partial F}{\partial v} S \frac{\partial \pi}{\partial F} - \epsilon \varrho v^{\varrho - 1} \tag{28}$$

$$\frac{\partial^2 \mathcal{L}}{\partial w \partial \lambda} = \frac{\partial F}{\partial w} S \frac{\partial \pi}{\partial F} + \gamma \mu w^{\mu - 1} \tag{29}$$

Now consider each of the diagonal elements in turn.

For the first diagonal element of the transformed matrix ((23)) we use the first order conditions ((6)) to substitute out terms. Then we can show that:

$$\frac{\partial^2 \mathcal{L}}{\partial v^2} = \frac{\partial^2 F}{\partial v^2} \left(1 - \lambda S \frac{\partial \pi}{\partial F} \right) - \lambda S \frac{\partial^2 \pi}{\partial F^2} \left(\frac{\partial F}{\partial v} \right)^2 - \frac{(\varrho - 1)}{v} \frac{\varrho}{\lambda} \left(\frac{\partial F}{\partial v} \left(1 - \lambda S \frac{\partial \pi}{\partial F} \right) \right) \tag{30}$$

This expression will be negative if product quality is concave in R&D investments $\frac{\partial^2 F}{\partial v^2} < 0$

and the first term in brackets is positive. The sign of the latter term depens on the shadow value of the constraint.

Solving equation (8) we can show that:

$$\lambda = \frac{\frac{\partial F}{\partial v}\frac{v}{\varrho} + \frac{\partial F}{\partial w}\frac{w}{\mu}}{S\frac{\partial \pi}{\partial F}\left(\frac{\partial F}{\partial v}\frac{v}{\varrho} + \frac{\partial F}{\partial w}\frac{w}{\mu} - \frac{F}{2}\right)} \tag{31}$$

It may be interesting to consider two simple cases here. Assume that $\varrho = \mu = 2$. Now consider the cases in which i) $u = v + w$ amd ii) $u = vw$. In the first case returns to not decrease sufficiently strongly and the constraint is only fulfilled if $v = w = 0$. Then companies can escalate spending until only a monopolist remains in the market. This company could escalate either advertising or R&D depending on which of the two mechanisms is more efficient.

The latter conclusion does not apply to the case of complements (ii)). Here the firm will escalate most effectively by combining advertising and R&D.

To be completed.