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ABSTRACT

Innovation and Market Structure: An Empirical Evaluation of the 'Bounds Approach' in the Chemical Industry*

This Paper empirically tests the 'bounds approach' to industry structure proposed by Sutton (1991, 1998). To carry out this task, we focus on the chemical industry. Part of the novelty in this exercise is that we work on the finest possible level of disaggregation. Also, we identify demand substitutability from direct industry sources. This allows us to carefully define markets, and identify R&D intensity for each of them. Our empirical specification allows us to simultaneously test the predictions of Sutton (1991) and Sutton (1998). Our results provide strong support to Sutton's theoretical framework.

JEL Classification: L11, L65 and O31
Keywords: bounds approach, chemical industry, innovation and market structure

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I. Introduction

Theoretical developments in industrial organisation (IO) and game theory during the last twenty years have greatly enhanced our understanding of the forces that shape micro economic outcomes. These advances have provided many insights, but at the same time, they have complicated the task of empirical researchers. Distinct modelling choices, such as the nature of competition or the treatment of fixed costs, have resulted in a wide array of possible outcomes. This has been one of the many factors contributing to the emphasis put on the analysis of single industry characteristics of the "new empirical industrial organisation" (NEIO, Bresnahan (1989)). By focusing on a single product, or closely related products, the task of modelling becomes somewhat easier, as industry characteristics may clearly indicate what the appropriate choices are.

While the NEIO has provided testable hypotheses, many of the issues identified by "traditional empirical IO" have remained unanswered. The latter's focus has been on a cross-section of industries, rather than a single set of products (Schmalensee (1989)). One issue that has received particular attention is the relationship between market structure and Research and Development (R&D) effort across industries. The existing empirical literature on this topic has provided mixed, if not contradictory, results (Cohen and Levin (1989)). Moreover, the Schumpeterian link between industry *concentration* and research effort has provided fuzzy results (Scherer (1990)).

Potentially, Sutton ((1991), (1998)) provides a unifying framework between these two traditions in empirical IO. On the one hand, his modelling approach makes extensive use of the game-theoretic tools that form the basis of theoretical developments in IO. On the other hand, his results are, under a set of reasonable assumptions, very general, as they encompass entire classes of models. This implies that the equilibrium concept does not include either a single or a reduced number of outcomes, but a wide variety of outcomes defined within a set of bounds.

Furthermore, one of the most interesting aspects of his approach is that his results point to testable hypotheses, both within industries, as well as across industries. For the purpose of this paper, his contributions provide clear-cut predictions on the relationship between market size, the existence of alternative technological trajectories in R&D intensive industries, and concentration. In particular, Sutton predicts first, that as market size grows, industries with endogenous sunk costs, such as advertising and R&D expenditures, may not evolve in equilibrium towards fragmented market structures. Second, high R&D intensity industries' minimum concentration levels are affected by consumers' heterogeneity of preferences, since the latter fosters the existence of alternative technological trajectories. In that context, the heterogeneity in research trajectories yields more fragmented structures.

The drawback of this approach is that it is extremely demanding in terms of data. Consequently, existing empirical work have focused on industries where markets (or sub-markets) can be easily identified. With respect to Sutton (1991), Lyons and Matraves (1996), Robinson and Chiang (1996), and Matraves (1999) perform empirical tests for several industries in the EU and the US that support Sutton's prediction about market size and market structure.

In his 1998 contribution, Sutton himself tests his theory using four/five and seven/eight digit US Census data, but recognises that this data presents some drawbacks. Indeed, it is necessary to assume that each seven/eight digit product(s) represent a technological trajectory within the market (the four/five digit level of aggregation). To our knowledge, there is no further work testing these predictions about technological trajectories and concentration.

Our results pertain to the chemical industry, which represents an important share of manufacturing output and employment. The interest of this industry is twofold. On the one hand, it encompasses different types of products in terms of the endogeneity of sunk costs, and a wide variety of consumer preferences. On the other hand, except for pharmaceuticals, advertising expenditures tend to be low since most products in the industry are not directed to final consumers. This allows us to clearly distinguish high from low R&D industries, and test the different predictions on these two types of industries. By combining distinct data sources, we hope to obtain precise measures for the relevant variables. In particular, we work at a very low level of disaggregation, namely chemical substances. By identifying alternative uses for these substances, we are able to characterise the degree of demand substitutability. This allows us to construct markets that are the empirical counterparts of those presented in Sutton (1998).

The paper is organised as follows: the next section reviews the theoretical literature and identifies a set of testable hypotheses. Section 3 applies this framework to R&D intensive industries. Section 4 describes the various data sets we make use of, and explains how the variables were constructed. Section 5 presents the results, while section 6 concludes.

II. Theoretical motivation

A brief review of the existing empirical evidence on the relationship between R&D intensity and concentration indicates that the results are at best mixed. Indeed, it seems that no solid empirical regularities can be detected in the data. There are various explanations to account for these findings. In what follows, we focus on two of them. The first is that R&D intensity may be a partial and incomplete measure of the technological characteristics of the industry. In particular, R&D intensity says very little on the nature of technological competition within an industry. The second, closely related explanation is that simple regression analysis is not the adequate tool to study the relationship between market structure and R&D intensity.

Most economic models are designed to provide a unique equilibrium in the space of relevant outcomes. Consequently, it is not possible to find a model that encompasses all possible types of competition and industry characteristics. On the contrary, we are faced with a set of models, each representing a specific situation, with each model providing a different, sometimes unique, equilibrium.

According to Sutton ((1991), (1998)) this is what occurs when analysing market structure in R&D intensive industries: a single model may be adequate, but only for a narrow subset of R&D intensive industries. The bounds approach is less demanding than this since it does not require the identification of a unique equilibrium. Rather, it focuses on the whole set of outcomes that could form part of the equilibrium. This method proceeds by eliminating the set of realisations that cannot belong to any equilibrium given a sensible set of assumptions. However, it is quite demanding, both theoretically and empirically, as it attempts to characterise whole sets of industries. If the set of possible outcomes is characterised by the bounds approach, this means that simple regressions are of no help in unearthing the underlying relationship between R&D intensity and industry structure. Quite simply, this is due to the fact that there is no unique mapping between R&D intensity and market structure in a cross-section of industries.

In order to characterise the set of possible outcomes, we need to define a stage game that represents firms' decisions. In the first period, that represents long run decisions, firms decide on entry and the level of sunk costs that they will incur (e.g., R&D expenditures related to a new product or process). The outcome may be a bundle of product characteristics, a set of locations, installed capacity, R&D or advertising expenditures. During the second period, that represents firms' short run decisions once entry has taken place and sunk costs have been paid, firms compete. Given any equilibrium configuration of products offered by different firms, there will be some corresponding set of equilibrium product prices, gross profit and industry sales. We thus need to identify which kind of configuration will be stable.

Clearly, there exists various ways to model each stage; the difficulty lies in the fact that there is no adequate discrimination process across models since the particulars of firms' decision process are not observable. Thus, the objective of the bounds approach is to reach conclusions independent of the form of competition and the entry process. In order to do so, it is necessary to relax the concept of sub-game perfect Nash equilibrium (SPNE). Accordingly, Sutton (1998) defines an equilibrium configuration such that it satisfies two conditions. The first is the "survival principle", which implies that firms are able to cover their fixed costs. The second is the "arbitrage principle". The latter refers to the fact that there are no empty spaces in equilibrium. Note that this concept is wider than the SPNE, since the allocation of each firm in the strategy space does not need to be optimal given other players' allocation. A direct implication is that this approach encompasses the concept of SPNE. This illustrates one of the main limitations of an SPNE solution: optimality can only be reached by specifying the characteristics of the entry process (e.g., simultaneous versus sequential entry), which are not observable. By contrast, an equilibrium configuration *à la Sutton* can be independent of these characteristics.

This setting can be applied to exogenous and endogenous sunk cost industries. With respect to exogenous sunk cost industries, firms' decision at stage one is related to entry and the number of varieties to introduce in the market. In the context of a horizontally differentiated product market (exogenous sunk costs case), it is easy to show that as market size increases, so does the number of products. Given that more competition (i.e. lower transport costs) implies lower price-cost margins, a larger market will be needed to attract entry since firms must pay their exogenous sunk costs with the profits that result from multiplying price-cost margins by sales. It is also the case that horizontal differentiation gives place to multiplicity of equilibria since one firm can produce several varieties of the product. Concentration increases in presence of scope economies, first mover advantages, and more homogeneity of consumers' preferences.

In the context of endogenous sunk costs, firms may spend on sunk costs (either advertising or R&D) in order to improve the characteristics of the products they sell. Suppose an entrant decides to spend K times more than its rivals on sunk costs. For each value of $K>1$, there is a corresponding number, a, such that the deviant firm achieves a profit of at least aY, where Y represents the ex-ante level of industry sales. Thus, the relevant variable is the highest value that the ratio a/K ratio can reach by choosing any value of K. Note that Sutton's framework, though very general, crucially rests on two assumptions.[1] First, consumers' willingness to pay for a given product can be enhanced to some minimal degree by means of a proportionate increase in R&D or advertising outlays. Second, these outlays must be fixed

[1] This argument applies in a context in which all consumers share the same ranking of preferences with respect to a specific characteristic of the product (quality).

(i.e. independent of the volume of output of the firm), have a small effect on unit costs, and be sunk (i.e. incurred at some earlier stage of the game and irrecoverable once the final stage is reached).

Sutton calls this ratio the "escalation parameter" and denotes it by $\alpha = a/K$. The main features of α are the following. First, it depends upon tastes and scope economies among products (the pattern of technology), and on the nature of price competition in the industry. Second, it measures the extent to which an industry consisting of many small firms can be destabilised by a firm outspending its many small rivals. Finally, it is independent of the number of firms in the industry (previous concentration). If α is high, this means that the deviant firm can capture at least some given share of industry revenue, independently of how many rivals offer the inferior quality product. Consequently, it sets a lower bound to both the 1-firm concentration ratio (maximal market share), and the sunk cost intensity of the industry's leading firm.

The intuition behind is the following. Note that both K and a are independent of market size. The costs of outspending rivals in sunk costs are K, but profits are aY, which are growing with Y (market size) for any $a>0$. Thus, given K, a, and market size, if firms have a very small market share, then it will be profitable for some firm to outspend its rivals' sunk costs and capture a larger market share. Hence, a configuration in which concentration lies below some critical value will be unstable. Therefore, it is possible to address two questions simultaneously: what determines concentration, and how are sunk cost intensity and concentration related?

This general view encompasses two types of endogenous sunk costs: advertising and R&D expenditures. Scope economies in advertising expenditures are large, since advertising campaigns have strong spillovers on all the range of products offered by one firm. Thus, the degree of substitutability among different varieties offered by a firm is not important in this case. The high quality firm is assumed to supply all the high quality varieties of the product. Accordingly, in advertising intensive industries concentration remains bounded away from zero as market size increases (Sutton (1991)).

However, when modelling R&D expenditures, these two variables become very relevant. When investing in one research trajectory, one firm may reach a high market share only when some conditions are met. Firms in the industry produce several groups of products that are imperfect substitutes not only in consumption, but also on the supply side, since they embody different technologies. In this case, R&D expenditures devoted to one group of products have limited spillovers on another group of products. Firms can develop many different technologies, each one related to a different group of products and must choose either to spend all their money on one trajectory or distribute it among several trajectories. This represents the choice between *escalation versus proliferation strategies*. In particular, α gives us the balance between these two alternative strategies. Clearly, the choice between the two will depend on economies of scope and substitutability among product varieties. A high substitutability among varieties of the product implies that consumers are willing to buy the superior quality variety. Alternatively, if there are strong scope economies in R&D, innovations can be applied to all product varieties made by the firm.

The determinants of α both stem from the supply and demand sides. With respect to the former, the relevant parameter is R&D's effectiveness in raising quality (consumers' willingness to pay for a higher quality product). From the demand side, it is the degree of substitutability among varieties resulting from different trajectories that plays a key role. If a set of products are close substitutes, escalating one technology helps cannibalising sales from alternative technologies, which makes the value of a higher; if they are poor substitutes, the value of a is lower. Therefore, we expect to observe higher concentration in industries with greater substitutability among product varieties. From the supply side, escalating technology allows firms to improve the quality of all product varieties. Again, we expect to observe higher concentration in industries with greater scope economies in R&D effort.

III. Empirical hypotheses

From an empirical point of view, the main difficulty consists in measuring a. With respect to R&D intensive industries, it is possible to identify two variables related to a which are: the R&D/Sales ratio, and the degree of proliferation of distinct research trajectories. The intuition behind the former is the following. If R&D expenditures are ineffective ($a \cong 0$, $a \cong 0$), then R&D intensity will be low. Consequently, we can deduce that industries with high R&D intensity are characterised by a high a.

The latter is related to the degree of demand substitutability across groups of products and can be proxied by industry fragmentation into distinct product classes, i.e. the fraction of the industry's sales revenue accounted for by the largest single product class. We will denote this homogeneity index by h.

High substitutability will imply high concentration. If all firms have small market shares, escalation of R&D expenditures along a trajectory will be profitable (the high-spending firm will capture sales related to its own and other firms' trajectories). Moreover, firms will operate along a reduced number of trajectories (for each firm it is better to concentrate efforts along a single trajectory and build efforts on other people's results). Therefore, h will be high.

Low substitution will imply that in spite of the effectiveness of R&D expenditures (high a), concentration may be low. This happens when there are many products associated to different R&D trajectories (low h). In this case, escalation does not lead to higher profitability, since market share is constrained to a single group of products. In such cases, a proliferation strategy is more effective in attaining a large market share.

Figures 1 and 2 below show lower bounds to concentration in exogenous and endogenous (R&D intensive) sunk cost industries depending on market size and substitutability. In non-R&D intensive industries, the fragmentation rises with market size and the degree of substitutability is not expected to affect concentration. By contrast, in R&D intensive industries, market size does not affect concentration and substitutability is negatively related to concentration.[2]

[2] As Sutton (1998) points out, one important aspect of this framework relates to the degree of aggregation. One could think that the whole matter could be solved by using the right degree of aggregation, so that by putting together products, which belong to different markets, we can arrive to the wrong conclusion that concentration is low in that market. However, this is not correct. First, it is difficult to define properly markets since some products are almost perfect substitutes for some consumers but very poor substitutes for some others. What would normally happen in markets where h is very low is that different products, which are broad substitutes, contain specific characteristics, which make them the only suitable for at least a small group of consumers. For this reason, firms can survive in the market despite the existence of new products that appear technologically superior in general terms. In such cases, the evolution of the industry tends to be characterised by the emergence of new products that are superior to the old product along some dimensions, but do not dominate potential substitutes in all dimensions. The appearance of these products triggers some temporary escalation in R&D expenditures until the possibilities of improving quality are exhausted. The important feature of these markets is that, once the exhaustion period has been completed, firms start re-addressing their efforts to new technologies and products. If we consider the new and old products as two different

Insert Figure 1 & 2 about here

IV. Data and variables from the chemical industry

Distinct markets where numerous firms are operating form the chemical industry. Each sector is characterised by a different R&D intensity and a different number of product classes, and presents a different market structure. With the exception of pharmaceuticals, advertising expenditures are not particularly relevant since most of their products are sold as intermediate inputs. Accordingly we believe that the analysis of the chemical sectors could shed some light about the robustness of Sutton's results related to R&D intensive industries.

The remainder of the section proposes and applies a methodology based on technological substitutability to map chemical substances into well defined markets. We then test the theoretical predictions of Sutton's (1998) model, and in particular, the relationship between market size, substitutability, and industry concentration. We expect to find concentration in high R&D intensive industries to be sensitive to the homogeneity index, h, measuring demand substitutability, and low R&D intensive industries to be sensitive to market size.

Our data set has been constructed by combining information from various sources. The "central" database is Chemintell, which provides detailed information on 36,343 chemical plants worldwide. Right from the start, we have excluded pharmaceuticals from the analysis, given that this sector operates under very idiosyncratic conditions (see Appendices 8.1 and 8.2 in Sutton (1998) and Matraves (1999) for a discussion). Also, the information provided in Chemintell does not permit a proper treatment of that sector (for instance, there is no information on whether the drug produced is a brand product still under patent protection, or if it is a generic drug).

Chemintell contains data on plant capacity (installed or planned), measured in metric tons, for most of the plants in the database. In a reduced number of cases, whenever data on capacity was not reported (but other information was available), we assigned the average capacity obtained from other plants producing the same substance. It also contains information on the location of plants, as well as the identity of their owners.

Of crucial importance for our purpose, the data pertains to chemical *substances* rather than final products. The database contains plants producing 2,279 different chemical substances that are grouped into 14 broad categories such as petrochemicals, organic chemicals, inorganic chemicals, and the like. Obviously, this aggregation is of no use for our purpose. To properly test the theory, it is of uttermost importance to define markets adequately. Demand side substitutability is a key parameter at the time of constructing markets. While each product may embody distinct technologies, what matters is the degree to which a given product is perceived as a substitute for other products in the same market.

The empirical work that we are aware of has used a simple method to define markets by making use of existing official classifications. Sutton (1998) follows that route by using data at the four/five and seven/eight digit levels, assuming that the former represents a market that contains the products of the latter. However we feel that there is room for improvement in the definition of markets, since four/five digit groups are too broad and include many different

markets, then we are not going to observe R&D expenditures properly, since most of the time they will be spent for products that do not yet exist.

markets. This is specifically true in the chemical industry. For instance, the four-digit group named "formulated pesticides" (CSO 2568), includes products such as fly paper (CSO 2568004), sheep dips (CSO 2568017), and plant hormones (CSO 2568014).[3]

We excluded many of the substances found in Chemintell either because they represented a minute proportion of the sample (e.g., a substance produced by only one plant in a non-OECD country), or because it proved impossible to obtain reliable information on their use. Thus, we examined, one by one, all possible outlets for the remaining 620 substances. The latter account for 63.1% of the total number of plants. The relevant information was retrieved from the RISC database that provides a detailed input/output table for the chemical sector at a very low level of disaggregation. We were thus able to identify downstream users for 200 of our substances.[4] For the substances that could not be classified using RISC, we relied on specialised publications, the Web, and trade journals. At the end of this process, we were able to identify 52 distinct groups of end-users, that is markets. We dropped 25 of them in order to err on the side of caution: end-users in these markets have access to substitutes outside the chemical industry (e.g.: textiles, cement and building, or automotive parts). While it may seem at first sight that we dropped many observations, this is not the case, as the –improperly defined- markets that we eliminated represent only a small proportion of the total number of observations. Our remaining 27 markets account for almost 50% of the plants found in Chemintell, and this proportion rises to 75% once pharmaceuticals are excluded. This information is summarised in table 1.

Insert table 1 about here

In most cases, a given substance was identified as having more than one possible use. Consequently, we had to decide how to allocate recorded capacity for each substance across our groups. We decided on a simple rule, namely to split capacity evenly among the groups in which the substance appears. This avoids ad-hoc judgements that would have been necessary in the event of choosing an alternative method.[5] With respect to geographical markets we use information on the five largest European markets: Germany, UK, Italy, France and Spain.

With this information we constructed the homogeneity index, *h*, as the percentage of installed capacity accounted for by the most popular substance within the sector. Substances are chosen to represent different technological paths, since they can be understood to be imperfect substitutes.

Before constructing the variables measuring concentration, we had to aggregate plant level information into firm level data. As mentioned above, Chemintell contains data on ownership, which we used to construct our firm level aggregate capacity for each group of substances. We crossed checked this information with the Amadeus database that contains balance sheet and ownership data for more than 200,000 European firms. With this

[3] CSO stands for the classification used by the British Central Statistical Office.

[4] RISC allowed us to classify 200 substances that account for a large proportion of installed capacity in the database. In addition, we were able to identify many end-uses for 111 substances not found in RISC, but that are known to be close substitutes on the demand side for substances identified in the database.

[5] An alternative is to assume that a 100% of capacity for a given substance can be allocated to each of the groups in which it appears. We tried that route, and the empirical results were qualitatively similar. We ended-up choosing the alternative proposed in the text because we feel it is more adequate.

information in hand, we were able to compute two measures of concentration, and in particular the one-firm (C_1) concentration ratio.[6]

The last step pertains to the partitioning of sectors according the R&D intensity. Unfortunately, Chemintell does not contain data on R&D expenditures. To alleviate this problem, we made use of Worldscope, a database that provides information on the 1,500 largest R&D spenders in Europe. We retrieved the R&D of all the firms that appear both in Worldscope and Chemintell. We then examined the product portfolio for each firm that appeared in Worldscope, using the information provided by Chemintell and assigned the firm level R&D intensities retrieved from Worlscope to each of the substances manufactured by these firms. In that exercise, the cut-off value we chose for R&D intensity is 1.8% (see table 2).[7]

Insert Table 2 about here

In most cases, it proved straightforward to determine the R&D associated with each substance. However, in some instances, markets were served by both high and low R&D intensity firms. This arose quite often when we were using information from multiproduct firms that were simultaneously active in pharmaceuticals. These firms often hold a wide product portfolio whose R&D intensities differ substantially (e.g. acids and vaccines).

Insert Table 3 about here

To alleviate this problem, we used an additional database on patents that contains information on 201,791 patents from the chemical sector. Using the fine disaggregation of the International Patent Classification (IPC), we were able to match the number of patents to our substances. We chose the cut-off value of 1,000 patents to classify a market as being R&D intensive.[8] This matched almost perfectly the classification that we had previously established with Worldscope.[9] We are thus confident that the splitting criterion that we used yields satisfactory results.

Insert Table 4 about here

Finally, in order to test the predictions of Sutton (1991) that, as market size increases, concentration tends to zero only for exogenous sunk cost industries, we had to construct a variable that measures the extent of the market. To this end, we proxied market size (denoted as *S*) by the sum of reported capacity of all the substances that form our markets. We then computed the size of the median plant in each of our markets, which yields an approximation

[6] The results are robust to alternative measures of concentration such as the four-firm (C_4) concentration ratio.

[7] 1.8% may appear as low at first sight; it should however be remembered that Worldscope provides R&D intensity for the entire firm. In the chemical sector, these are typically large multiproduct firms, which tends to depress measured R&D intensity.

[8] The cut-off value of one thousand patents splits markets in a clear-cut manner in the sense that there are no sectors with patents close to that number. It is either much higher, or much lower.

[9] Of the markets with more than a 1,000 patents, only 3 (Gas Handling, Fuels, and Film) displayed an R&D intensity below 1.8%. Given the nature of these products, the "multiproduct" effect depresses observed R&D intensities. In these three product groups, large R&D expenditures are dwarfed by the volume of sales (Fuel and Gas Handling), or by sales of low R&D products manufactured by the same firm (Film). By contrast, products with less than a 1,000 patents all had intensities well below 1.8%.

of the minimum efficient size of operation (denoted by *MES*), that is, of exogenous sunk costs. Thus, the variable that measures the extent of the market is defined as the natural logarithm of S over *MES*, i.e. ln(S/*MES*).[10]

V. Empirical results

V.1 Statistical analysis

Our results pertain to the relationship between market concentration, market size, and the homogeneity index. Since we have both high and low R&D intensity industries, we can compare the results for these two groups. Diagrammatical results can be visualised in Figures 3a,b and 4a,b. Figure 3a and 3b present the relationship between concentration and the market size to set up costs ratio for the five largest European countries, namely Germany, France, the UK, Italy and Spain. The variable C_1^* is defined as:

$$C_1^* = \ln \frac{C_1}{1 - C_1}$$

In Figure 3a, we have a plot relating the extent of the market to the degree of concentration in low R&D industries (that is, exogenous sunk costs industries). As can be readily seen, concentration falls as market sizes increases.

Insert Figure 3a & 3b about here

Figure 3b provides the same information, but for high R&D industries (that is, endogenous sunk cost industries). In contrast to 3a, concentration stops declining once a market size threshold is reached. Given that both figures use the same scale, they can be directly compared.

In order to estimate lower bounds, Sutton (1991) suggests a methodology based on Smith (1985, 1994), that we apply to these two sets of observations. This involves a two-step procedure. First, we need to decide on the schedule that describes the lower bound. The family of schedules chosen by Sutton is the following:

$$C_1^* = d + \frac{b}{\ln(S / MES)} \qquad (1)$$

The fitted schedules are illustrated in figures 3a and 3b. The relationship between the two schedules gives support to the predictions of the theory as presented in figure 1.[11]

Second, we need to check that the associated set of residuals fits a Weibull distribution.[12] This type of distribution can be written as

$$F(x) = 1 - \exp\left[-\left(\frac{e - m}{d} \right)^b \right] \qquad b > 0, d > 0 \qquad (2)$$

[10] The use of this variable may involve a potential bias since concentrated industries are characterised by large firms that operate large plants (see Davies (1980)). Note however that the main purpose of this paper is to test Sutton's (1998) predictions, which are independent of ln(S/MES). Furthermore, in our sample, there is no evidence of such a correlation for the full sample (correlation(ln(S/MES;C_1)=-0.036), or across industries at the country level, or across countries at the industry level.

[11] Robinson and Chiang (1996) propose alternative schedules that are consistent with Sutton's theoretical predictions. These schedules also fit our data.

[12] Sutton (1991, pages 115-116) provides a detailed explanation on the suitability of the Weibull distribution.

where $e \geq m$ represents our set of residuals, b is a shape parameter (lower values of b correspond to a higher degree of clustering of observations at the lower bound), d is a scale parameter and m is a location parameter. The case of m =0 corresponds to the two parameter Weibull distribution. If the residuals follow a Weibull, then the scatter plot in Figure 5a, where $M_i = e_i - m$, should be a straight line.[13] The visual analysis clearly indicates that we can safely assume that the set of residuals is indeed well approximated by a Weibull.

Table 5 presents the numerical results. To test the null hypothesis that the estimated schedules for both types of industries converge to the same value as $S/MES \rightarrow \infty$, we can look at the difference between the $C^*_{1,\infty}$. Given the values for the standard errors of m, the hypothesis can be rejected. In particular, the limiting value of the estimated bound when $S/MES \rightarrow \infty$ corresponds to a value of C_1 = 3.33 for the low R&D group and C_1 = 12.04 for the high R&D group.[14] With respect to the value of b, we find a higher slope for low than for the high R&D group, as predicted by the theory. Additionally, the values of m correspond to the three parameter Weibull distribution and the ΔNLLH indicates the difference in the negative log likelihood between the three and the two parameter Weibull. The two parameter Weibull cannot be rejected at the 5% level. Finally, the estimated value of b for high R&D intensive industries is below 2, which indicates that Smith's (1985) methodology must be chosen since a maximum likelihood approach is inadequate in such cases (b<2). The main shortcoming of this approach is that the results depend crucially on the functional form chosen for the frontier and on the presence of outliers. Still, our results do not contradict the theoretical conjectures and are consistent with those of Sutton (1991).

Insert Table 5 about here

In Figure 4a and 4b, we relate concentration to our homogeneity index. For the low R&D intensity group, we observe a random scatter plot, which is consistent with the theoretical predictions. By contrast, in high R&D intensity markets, no observations are found in the South-East corner, suggesting the existence of a bound. Note that the empty space in the South-East may reflect the existence of scope economies as suggested by Sutton (1998, Appendix 3.2).

Insert Figure 4a & 4b about here

In this case Sutton (1998) proposes an alternative statistical test.[15] The basic idea is to test if in R&D intensive industries, C_1 is bounded away from zero as h increases. Before turning to the statistical analysis, we apply the following transformations:

$$C_1^{'} = \ln \frac{1}{1 - C_1}$$

$$h^{'} = \ln \frac{1}{1 - h}$$

[13] To do this plot, define $M_i = e_i - m$, given a reasonable value for m, and rank M_i in ascending order. Then define the cumulative distribution function as $F(M_i) = i/n$, where i denotes the position in the ranking and n the sample size. If M_i are defined as a two parameter Weibull distribution, a plot of $\ln(\ln(1/(1-F(M_i))))$ against $\ln M_i$ yields a straight line.

[14] These results are very similar to those reported in Robinson and Chiang (1996).

[15] Note that this second test does not suffer from the limitations of the first test mentioned above.

so that $C_1^{'}$ and $h^{'}$ are distributed in the interval (0, +∞).

We assume that the ratio $C_1^{'} / h^{'}$ follows a Weibull distribution. As we know, the validity of this assumption can be easily checked. If the ratio does follow a Weibull, then the scatter plot in Figure 5b, where R = $C_1^{'} / h^{'}$ - m, should be a straight line. This analysis suggests that the ratio is well approximated by a Weibull.

Insert Figures 5a and 5b about here

If a random variable is drawn from a two-parameter Weibull distribution, then its natural log follows an extreme value distribution. We can thus apply the Mann-Scheuer-Fertig test to the null hypothesis that the lower bound is equal to zero. As before, the Weibull distribution is given by equation (2), now with $e = \ln(C_1^{'} / h^{'})$.[16]

The basic intuition behind this test is the following. If the Weibull distribution is not bounded away from zero, i.e. $m = 0$, then it can be transformed into an extreme value distribution in the space (-∞, +∞). However, if the Weibull distribution is strictly bounded away from zero, i.e. $m > 0$, then it transforms into an extreme value distribution that is truncated on the left. The issue is then whether our empirical distribution is adequately approximated by such an extreme value distribution.

The Mann-Scheuer-Fertig test proceeds as follows. Define the spacing, or leaps, between ranked observations as:

$$l_i^{'} = \frac{e_{i+1,n} - e_{i,n}}{E(e_{i+1,n}) - E(e_{i,n})}$$

where E stands for expected value. Assume that ε follows an extreme value distribution with location parameter $m = 0$ and compute $E(e_{i,n})$ accordingly. Then divide the sample at the midpoint and compute the following test statistic:

$$TS = \frac{\sum_{i=n-r}^{n-1} l_i^{'}}{\sum_{i=1}^{n-1} l_i^{'}}$$

where r equals the integer part of (n-1)/2. Note that if our Weibull distribution is not bounded away from zero TS≅0.5. The asymptotic distribution of TS is a Beta distribution, so that the observed value of TS can be compared to the percentile value of the Beta distribution (Harter (1964)).

Applying this test to our sample yields a value of TS=0.74, which results in rejecting the null hypothesis that $C_1^{'} / h^{'}$ is not bounded away from zero at the 1% level. This finding confirms our previous results, and is consistent with Sutton (1998).

V.2 Frontier analysis

We obtain confirmation of these findings by carrying-out a simple econometric exercise, in which we estimate a stochastic frontier. This involves imposing a structure on the residuals to test whether observations lie on the correct side of the frontier. Consequently, our error term is made-up of two components independent of each other and defined as follows. The first, denoted by v, is a symmetric component that measures random variations of the frontier across observations and captures the effects of measurement error, other statistical

[16] See details in Sutton (1998)

noise, and random events. The second, named u, is a one-sided component greater or equal than zero that captures the distance of the observation from the frontier. We can assume several possible distributions for this component, such as a half-normal or half-exponential.

When trying to explain concentration in high and low R&D intensity industries, we expect opposite results. In particular, for low R&D industries (exogenous sunk cost industries) we expect the coefficient on the homogeneity index, h, not to be significantly different from zero, while market size is expected to affect concentration negatively. By contrast, in high R&D industries, the coefficient on h should be significantly positive while it should not be affected by market size. Accordingly, the equation to estimate can be expressed as follows:

$$C_1^* = l_0 + \frac{l_1}{\ln(S/MES)} + l_2 h^* + v + u$$

where $h^* = \ln \dfrac{h}{1-h}$, and the l's the parameters to be estimated.

The results, assuming that u follows a half-exponential distribution, are presented in Table 6.[17] As can be readily seen, this frontier analysis yields coefficients of the expected sign and significance, consistent with our previous analysis.

Insert Table 6 about here

VI. Conclusions

The theoretical developments presented by Sutton in his 1998 contribution provide a general framework to explain the relationship between market structure and innovation. To our knowledge, leaving aside the evidence presented by Sutton himself, this is the first contribution testing his predictions.

In order to carry out this task, we have concentrated on the chemical industry. The latter is particularly suited for our purpose because it encompasses many different products characterised by distinct R&D intensities and alternative research trajectories. Moreover, many chemical are primarily sold as intermediate inputs in the production process and therefore present low levels of advertising intensity.

We have constructed our sample for the chemical industry starting from a very disaggregated level in order to obtain empirically meaningful variables. This also allowed us to group products according to the degree of demand side substitutability, which is what Sutton's theoretical framework dictates.

Our database permits a simultaneous test of Sutton (1991) and Sutton (1998). Both statistical tests proposed by Sutton and alternative econometric approaches provide strong support to the underlying theory.

[17] The results pertaining to a half-normal are qualitatively identical.

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FIGURES

Figure 1. Lower bounds to concentration in exogenous and endogenous sunk cost industries.

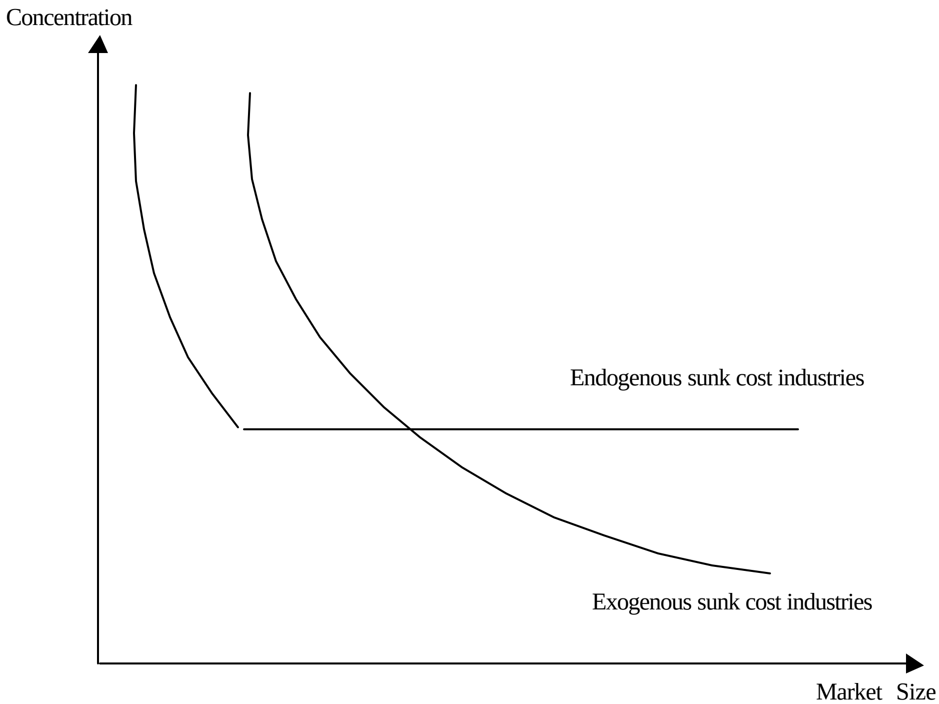


Figure 2. Lower bounds to concentration in high and low R&D intensity industries.

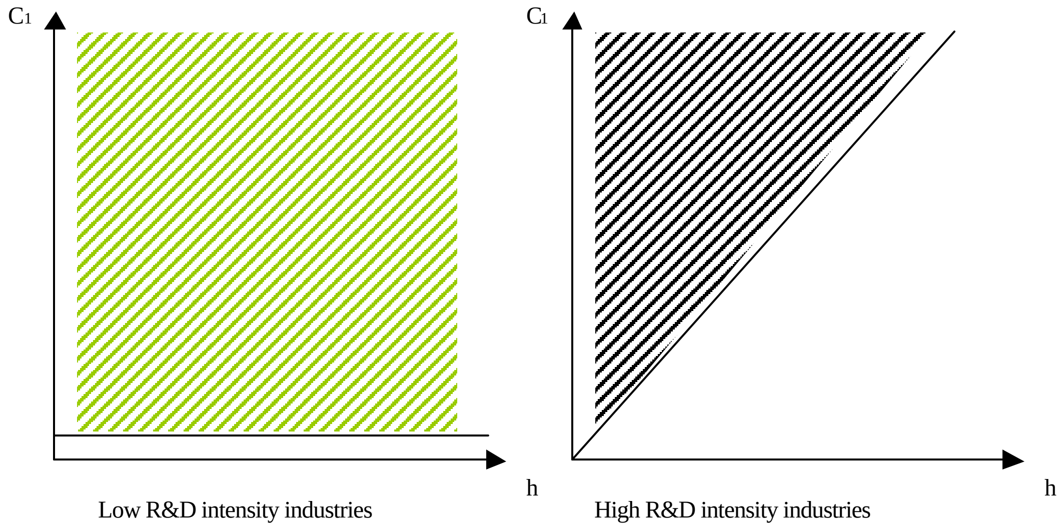


Figure 3a. Low R&D intensity industries

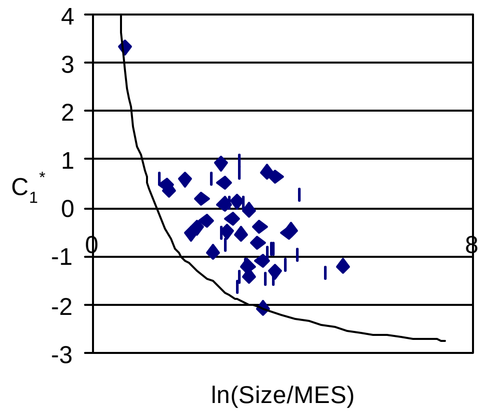


Figure 3b. High R&D intensity industries

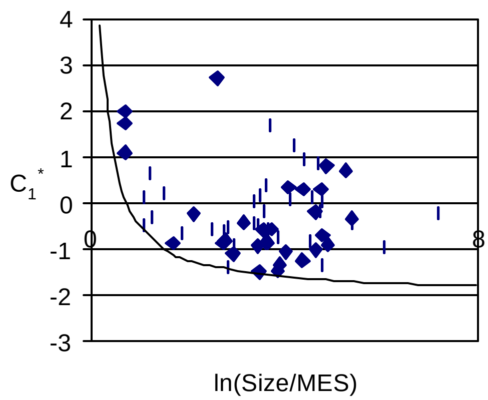


Figure 4a. Concentration and homegeneity in low R&D industries

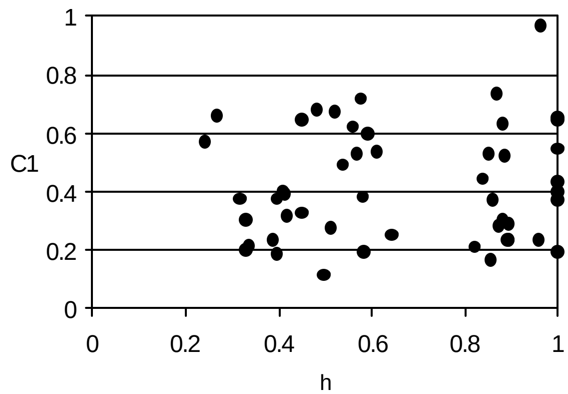


Figure 4b. Concentration and homegeneity in high R&D industries

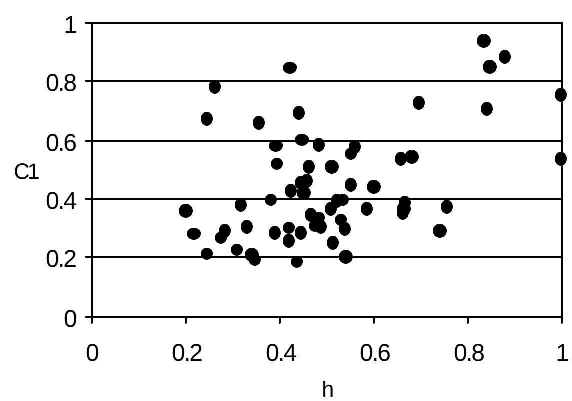


Figure 5a

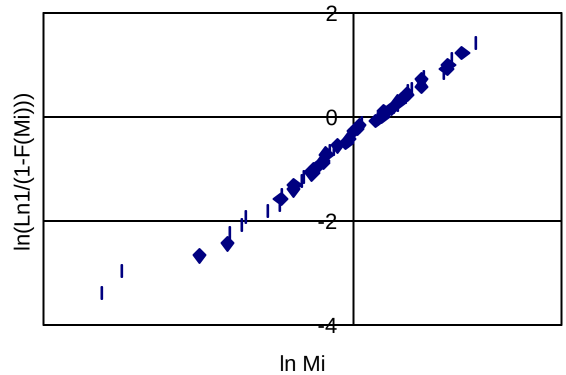
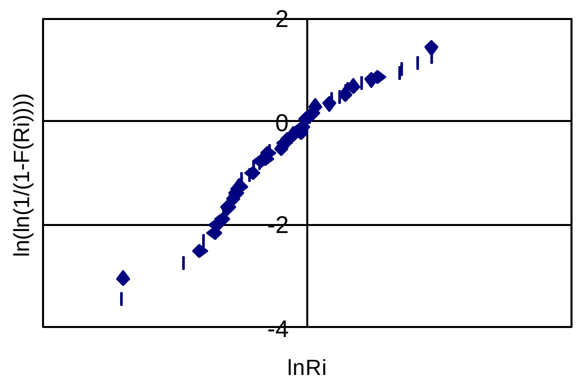


Figure 5b



TABLES*

Table 1. Chemical substances analysed

	CHEMINTEL	52 Markets	27 Markets
Substances	2279 (100%)	620 (27.2%)	429 (18.8%)
Plants	36343 (100%)	22941 (63.1%)	17699 (48.7%)

Source: Chemitell database and own calculations

Table 2. Data on R&D intensity retrieved from Worldscope

Markets	SIC code	Description	No. of firms	Weighted R&D to sales ratio[1]	Max. R&D to sales ratio[2]	R&D/Sales of the largest firm[3]
Tyres	3011	Tires and inner tubes	4	3.76	4.00	4.00
Adhesives	2891	Adhesive & sealants	3	2.95	4.07	3.33
Dyes	2816	Inorganic pigments	1	1.56	2.09	1.56
	2865	Cyclic organic crudes, intermediates, organic dyes, & pigments	8	6.75	7.66	6.96
	Total		9	6.53	7.66	6.96
Fibres	2823	Cellulosic manmade fibers	3	3.10	4.89	3.48
	2824	Manmade organic fibers, exc. cellulosic	2	1.50	2.27	1.58
	Total		5	2.58	4.89	3.48
Agrochemicals	2879	Pesticides & agric chem., n.e.s.[a]	3	2.77	8.94	0.95
Paints	2851	Paints, varnishes, lacquers, enamels & allied products	8	1.87	5.34	1.90
Rubber	2822	Synthetic rubber	1	1.17	1.91	1.17
	3021	Rubber & plastic footwear	2	2.59	2.59	2.59
	3052	Rubber, & plastic hoses & belting	2	3.49	4.28	1.05
	3061	Molded, extruded & lathe-cut rubber	1	1.73	2.19	1.73
	3069	Fabricated rubber n.e.s.	4	2.55	3.68	3.37
	Total		10	2.43	4.28	3.37
Alloys, Coinage, Batteries	1021	Copper ores	1	2.03	2.84	2.03
Lubricants	2992	Lubricating oils & greases	3	1.93	2.39	2.12
Film	3081	Unsupported plastics film & sheet	1	0.07	0.12	0.07

Table 2 (Cont.). Data on R&D intensity retrieved from Worldscope

Markets	SIC code	Description	No. of firms	Weighted R&D to sales ratio[1]	Max. R&D to sales ratio[2]	R&D/Sales of the largest firm[3]
Fuel	1221	Bituminous coal & lignite surface mining	1	2.42	2.42	2.42
	1222	Bituminous coal underground mining	2	0.76	2.23	0.67
	1311	Crude petroleum & natural gas	9	0.83	5.15	0.75
	1321	Natural gas liquids	2	0.41	0.63	0.41
	1381	Drilling oil & gas wells	1	2.19	2.19	2.19
	1382	Oil & gas field exploration services	2	0.97	1.97	0.70
	1389	Oil & gas field services, n.e.s.	2	1.37	3.15	0.56
	Total		19	0.76	5.15	0.67
Gas handling	1321	Natural gas liquids	2	0.41	0.63	0.41
Coatings	2952	Asphalt felts & coatings m	1	0.50	0.74	0.50
Fertilizers[4] (exc. nitrogenous)	2875	Fertilizers, mixing only	1	0.51	0.58	0.51
Soap	2841	Soap & other detergents, exc. specialty cleaners	1	1.33	1.44	1.33
Surfactants	2843	Surface active agents, finishing agents, sulfonated oils & assistants	2	1.21	1.79	1.21
Nitrogenous fertilizers	2873	Nitrogenous fertilizers	3	1.34	2.08	1.03

Source: IPC, Worldscope and Chemintell databases, and own calculations

[a] n.e.s.: Not elsewhere specified

[1] Weighted average for all firms during the six years of data.

[2] Maximum reported by firms during the six years

[3] Weighted average for the largest firms during the six years of data, with size measured as sales during the last year of data.

[4]: This market groups Potassium, Phosphorous, and Sulphur fertilizers

Table 3. Percentage of substances to which an International Patent Classification code could be assigned

Markets	Number of substances	No. of subs. with assigned IPC code	% of subs. with assigned IPC code
Gas handling	69	20	29%
Fuel	73	18	24.7%
Agrochemicals	51	43	84.3%
Film	37	9	24.3%
Fibres	45	5	11.1%
Paints	13	5	38.5%
Sulphur fertilizers	14	7	50%
Nitrogenous fertilizers	29	19	65.5%
Phosphorous fertilizers	22	14	63.6%
Potassium fertilizers	16	9	56.3%
Alloys	10	7	70%
Soap	20	10	50%
Dyes	19	12	63.2%
Adhesives	46	14	30.4%
Disinfectants	5	4	80%
Rubber	4	2	50%
Coatings	21	6	28.6%
Tyres	7	2	28.6%
Lubricants	20	7	35%
Batteries	4	3	75%
Surfactants	9	1	11.1%
Anaesthetics	3	0	0.0%

Source: IPC and Chemintell databases, and own calculations

Table 4. Markets with more than 1,000 patents

Markets	Number of substances	No. of subs. with assigned IPC code	% of subs. with assigned IPC code	Number of patents
Gas handling	69	20	29%	8191
Fuel	73	18	24.7%	7550
Agrochemicals	51	43	84.3%	11236
Film	37	9	24.3%	1102
Lubricants[1]	20	7	35%	1632

Source: IPC and Chemintell databases, and own calculations

[1] The substances forming this market, did not total one 1000 patents. However, we did find an IPC class with 1632 patents that corresponded to our market "Lubricants", but included a larger number of substances.

Table 5. Estimation of lower bounds for market concentration as market size grows.

	d= $C^*_{1,\infty}$	b	$C_{1,\infty}$	m	ΔNLLH	b
Low R&D	-3.37	4.64	3.33	$-3t10^{-6}$ ($70t10^{-6}$)	0.000	2.16 (0.24)
High R&D	-1.99	1.65	12.04	-0.02 (0.012)	0.004	1.48 (0.15)

Note: Standard errors in parentheses

Table 6. Frontier estimations, dependent variable: C^*_1

Variable	Low R&D intensity	High R&D intensity
Constant	-1.55 (0.24)	-1.07 (0.14)
$\frac{1}{\ln(S\,/\,MES)}$	8.49 (2.05)	1.00 (1.04)
h^*	-0.01 (0.10)	0.33 (0.15)
Number of observations	42	60
σ^2_v	0.16	0.09
σ^2_u	0.43	0.60

Notes: Standard errors in parentheses