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# Vertical Organization, Technology Flows and R&D Incentives - An Exploratory Analysis

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ABSTRACT

**Vertical Organization, Technology Flows and R&D Incentives**
**An Exploratory Analysis**

by Dietmar Harhoff*

Despite its importance, the impact of vertical organization on innovation incentives has not been investigated in depth. This paper develops a number of testable hypotheses and then provides a first exploratory empirical analysis, using cross-sectional industry-level data. Two simple stylized facts emerge from the empirical results. First, once a fragmented buyer industry is dependent on a relatively concentrated supply sector, the industry’s own R&D intensity is reduced substantially. Second, vertical technology flows appear to act as substitutes for an industry's own R&D if the receiving industry's concentration is relatively low. Both results are largely consistent with a number of case studies and with theoretical arguments discussed in the paper.

ZUSAMMENFASSUNG

**Vertikale Organisation, Technologieflüsse und FuE-Anreize -**
**Eine explorative Studie**

Der Einfluß der vertikalen Organisation von Industrien auf Innovationsanreize ist trotz der Bedeutung der Fragestellung noch nicht detailliert untersucht worden. Dieses Papier stellt eine Reihe von testbaren Hypothesen vor und präsentiert eine erste explorative empirische Analyse auf der Basis eines Querschnittsdatensatzes. Zwei empirische Regularitäten können nachgewiesen werden. Zum einen liegt die FuE-Intensität einer Industrie erheblich unter dem üblichen Durchschnitt, wenn die Konzentration der Industrie niedrig ist, aber eine Abhängigkeit von einer konzentrierten Zuliefererindustrie besteht. Zum zweiten scheinen vertikale Technologieflüsse als Substitute für die eigene FuE einer Industrie zu fungieren, sobald die Konzentration der Empfängerindustrie relativ niedrig ist. Beide Resultate sind prinzipiell konsistent mit weiterer Evidenz aus Fallstudien und mit den theoretisch hergeleiteten Hypothesen.

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## 1 Introduction

This paper studies the relationship between the structure of supply sectors, vertical technology flows and the R&D incentives of firms in downstream buyer industries. While much of the work in the Schumpeterian tradition has focused on determinants of R&D incentives within a given industry, little research has been produced on the effect of inter-industry linkages, and of vertical organization in particular. The purpose of this paper is to analyze whether the relationship between the structure of a supply industry and the structure of a downstream industry has some bearing on downstream R&D incentives. The main theoretical basis for presuming that such a relationship exists should not be controversial. In any vertical channel of economic activities, rents are being generated and shared horizontally between firms in a given industry. But the vertical rent distribution between the participating industries may also have a bearing on R&D incentives. Firms in any industry may behave strategically to increase the share of rents accruing to their own industry. If these rents have to be shared with many competitors, then naturally the respective incentive is weak. If one firm dominates an industry or has obtained a monopoly position, then this incentive is comparatively strong.

Some of the modern insights of the innovation literature can be summarized by saying that R&D incentives largely follow appropriability. Loosely speaking, the party that can obtain the largest share of the rents from innovation is also likely to assume the burden of the necessary investment. Applied to the question at hand, this leads to the hypothesis that firms which dominate and profit most from a vertical channel of production activities also make the investments that enhance the profits generated in this channel of activities. By implication, this argument suggests that other firms tend to invest comparatively less.

Based on detailed argument how supplier firms can affect the vertical rent distribution in their favor, this paper identifies cases of vertical organization in which these incentives are particularly strong. If a supply sector is organized as a monopoly or a highly concentrated oligopoly, and if the profitability of such producers depends highly on sales to a particular downstream sector, then these firms are likely to contribute to downstream productivity enhancement to increase their profits. In these cases, the locus of innovation should shift to upstream sectors.

Moreover, this paper argues that the respective supplier firms may act strategically by using disembodied knowledge to encourage entry or by distributing technical information to maintain a competitive downstream industry structure. Finally, suppliers may attempt to preempt major technical advances in downstream industries to prevent the emergence of a more concentrated industry structure. Theory suggests that all of these strategies have a relatively high payoff to the supply sector firms, if the ex ante structure of the downstream sector is close to the competitive ideal. Finally, if such situations arise, suppliers may also have strong incentives to structure tangible flows of technology (i.e.

know-how that is embodied in their products) such that they act as substitutes for downstream R&D.

The regression results described here strongly support the view that supply sector organization has a significant role in shaping downstream R&D incentives. I find that fragmented buyer industries which receive relatively large cost shares of their inputs from concentrated supply sectors have a significantly lower R&D intensity than sectors relying on more competitive supply structures. Furthermore, relatively concentrated downstream sectors are not subject to this effect. The regression results are also consistent with the hypothesis that firms in fragmented industries use the inflow of technology from suppliers as a substitute for their own R&D, but this effect is weakened and eventually reversed as the concentration of the downstream industry increases.

The remainder of this paper is structured into four sections. In Section 2, I briefly summarize the existing literature on interindustry technology flows, in particular the contributions by Scherer (1982), Pavitt (1984) and Farber (1981). Testable hypotheses based on the literature and on my own theoretical work are developed in Section 3. Section 4 employs a simple linear specification for a regression analysis of R&D intensity, using industry-level data from the Federal Trade Commission which is matched with qualitative data from the Yale Survey. Implications and limitations of this research are discussed in Section 5.

## 2 Vertical Organization, Interindustry Technology Flows, and R&D Incentives

### 2.1 A Review of the Empirical Literature

Interindustry technology flows and the vertical organization of production activities have not played a major role in recent theoretical and empirical work on innovation and technological change. This fact is quite surprising, given that institutionally oriented researchers (Pavitt 1984; von Hippel 1988) have produced persuasive evidence that the composition of supply sectors is often correlated with distinct innovation patterns within a given industry. Structural changes in the American economy have also been linked to changes in input and output flows in Carter's (1970) extensive analysis. In recent econometric studies, Levin and Reiss (1988), and Cohen and Levinthal (1989) have included in their models variables that account for the contributions to innovation made by external sources of technology, e.g. equipment and materials suppliers. But all of these studies have treated the contributions originating in other sectors as exogenously given. The interdependence between R&D incentives of firms in different industries is not yet fully understood.

The importance of R&D performed by other sectors for an industry's productivity growth was demonstrated as early as 1967 in research by Brown and Conrad (1967). Regression studies by Raines (1971) and Terleckyj (1974) confirmed the Brown-Conrad result, but they also produced some unexpected estimates. Raines and Terleckyj found that R&D embodied in intermediate and capital goods was a statistically significant determinant of an industry's productivity, but that the industry's own R&D was no longer significant once the measure of embodied R&D was included.[1] However, the measures for embodied R&D used in these early studies do not inspire great confidence. R&D expenditures of a supplier industry are simply distributed according to the distribution of purchases by downstream industries. The true allocation of upstream R&D resources probably differs from the one implicitly assumed in these studies.

Two extensive empirical studies (Pavitt 1984; Scherer 1982) have provided us with a more precise and detailed description of interindustry technology flows. Scherer (1982) conducted a major effort to map the technology flows between industries in the United States economy and produced a detailed technology flow matrix. The idea of such a matrix dates back to Schmookler (1966), who used patent data to calculate measures for the rate of production and consumption of novel technologies in several industries. Scherer's efforts were similar, but produced data at a far greater level of detail. Using 443 large US corporations reporting under the FTC line of business survey as his sample, Scherer and associates analyzed the specifications of all 15,112 patents that were obtained by these firms in the period between June 1976 and March 1977. Among other information, patent specifications include data regarding the prospective use of the patented technology. The value of the patent was approximated as the average (per patent) R&D expense incurred by the inventor. The flow variable constructed by Scherer measures then the innovator's R&D expenditures flowing to the sector using the new technology. Each industry is conceivably a user of technology produced by other industries and conversely produces technology for use by other sectors. The technology flow matrix captures these flows in a simple way.

Patents are used in this data construction effort to allocate an industry's R&D expenditures to a sector of use.[2] The measure of total R&D use can be calculated under

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1 A more detailed discussion of these issues is given by Nelson and Winter (1977). Nelson and Winter provide several explanations for this counterintuitive result, but all of their arguments are based on the assumption that some variables are measured with error. The theoretical model developed by Harhoff (1996) seems to imply another explanation: an industry's productivity and the R&D content of inputs may be determined endogenously. The coefficient on the variables measuring the R&D content of inputs will then be biased.

2 Industry- and technology-based idiosyncrasies in patenting behavior will therefore not necessarily create a bias as long as the overall distribution of patents across sectors of use is not affected. But there are other measurement issues. Scherer (1984) describes some of the problems that had to be solved in order to allocate R&D meaningfully to using sectors. Other aspects of this dataset are discussed in detail by Scherer (1984) and

two alternative assumptions. If the R&D results produced in one sector and transferred to several other industries have public goods characteristics (*public goods* assumption), then all recipients are credited with the origin industry's R&D expenditures weighted by a correction factor that reflects differences in the purchasing volume of the product embodying the R&D knowledge. Under the *private good* assumption, the R&D flows received by the using industries add up to the origin industry's R&D expenditures. Scherer calculated both data series for over two hundred industries.

A particularly difficult problem is the allocation of R&D to own process improvements. It is reasonable to assume that process innovations are often not patented and instead protected by secrecy. This would lead to a downward bias in the ratio of patents indicating internal use of R&D resources. But comparing his estimates to those of two alternative data sources (McGraw Hill research and development expenditure surveys and the PIMS data base of the Strategic Planning Institute), Scherer finds no evidence that the process R&D share measures are seriously biased.

Scherer's results suggest that there is considerable variation in the ratio of R&D produced to R&D consumed. Sectors like lumber and wood products, ferrous metals, textiles, and apparel and leather are characterized by low origin to use ratios. Conversely, industries like farm machinery, computers and office equipment, construction and mining machinery, or instruments produce several times as much R&D than they consume.

Results very similar to these are provided by Pavitt (1984), who uses data on about 2000 significant innovations introduced in the British industry between 1945 and 1979 to analyze sectoral patterns of innovation. For each innovation, he identifies the sector in which the innovation originated, the sector of final use, and the sector of the firm's principal activity. As in Scherer's work, the interindustry technology flows can be identified, though their measurement is now based on the number of significant innovations rather than expenditure-weighted patent counts. Based on his data, Pavitt proposes a taxonomy of three distinct patterns of innovation: supplier dominated innovation, innovation that largely depends on large-scale production, and science-based innovation.

Pavitt suggests that innovation in industries like agriculture, construction, textiles, lumber, wood and paper mill products, and printing and publishing originates mainly with suppliers of equipment and materials. Firms in the respective sector make only minor contributions to their own product and process technology. According to Pavitt, these

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in a comment by Mansfield. For example, it is well-known that patents can be of different value and importance. This view has been confirmed in a number of studies using patent renewal data, e.g. Pakes (1986). A recent study of German patents comes to the conclusion that patent renewal studies may even underestimate the skewness of the patent value distribution (Harhoff, Scherer, and Vopel 1998).

firms tend to be small and have only limited internal R&D capabilities. Conversely, production-intensive firms operate on the basis of large-scale technologies that allow for considerable economies of scale. But these economies are *latent*, i.e., they do not emerge automatically, but are achieved at the cost of internal efforts which are often undertaken by specialized production engineering departments.[3] Innovation in scale-intensive sectors may also originate with relatively small and highly specialized input suppliers (e.g. for instrumentation or process equipment). Finally, Pavitt identifies *science-based* sectors in which firms rely heavily on their own R&D efforts which are closely linked to progress in underlying sciences like chemistry, biology, or physics (among others). A recent example of such a sector is the emerging biotechnology industry in which several new enterprises were founded by university researchers.

The contributions by Scherer and Pavitt are noteworthy for several reasons. Both use samples from different countries and different underlying measures for innovative output. Nonetheless, a number of patterns detected in their data are emarkably similar. Both studies provide some support for the notion that R&D results are embodied in an industry's output and that buyers can often enjoy considerable benefit spillovers due to imperfect appropriability by firms in the producer industry. Furthermore, the sectors identified as net users or net producers of innovative technology match each other closely.[4] But it is also clear that the precise measurement of these effects is a difficult matter. Furthermore, the determinants of the interindustry technology flows described by Scherer and Pavitt are still poorly understood. For many practical purposes, the descriptive account of technology flows proves immensely helpful and sufficient. But it is of great theoretical interest to probe deeper and explore the *endogenous* determination of these flows. One way to approach this question is to explore the interdependence between R&D incentives of firms in vertically related industries. This is done in the next section.

Farber's (1981) study is to my knowledge the only empirical effort to shed some light on this question.[5] Farber analyzes the effect of buyer market structure on the R&D incentives of seller industries and considers several effects of buyer market structure on the seller's rent expectations, e.g. the magnitude of rents, their appropriability, and the speed of adoption of technologies in the buyer industry. Using a model originally developed by Demsetz (1969), Farber suggests that the magnitude of innovation rents is greater if the buyer market is more monopolistic. With respect to appropriability and

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3 A detailed discussion of such efforts is given by Levin (1977) and Rosenberg (1976). The term *latent economies of scale* originates with Levin.

4 A comparison between these results is provided in Pavitt (1983).

5 Some theoretical work preceding Farber's study can be found in Binswanger and Ruttan (1978) who discuss a supplier's incentives to create a bias in the direction of technological change.

speed of adoption, he argues that increased concentration on the buyer's side is likely to discourage seller R&D efforts, in particular if the seller market itself is competitive. Farber's main argument is based on the notion that price discrimination is facilitated in settings where few sellers face many buyers. Farber then estimates a simultaneous equations system for R&D intensity (measured as employment of engineers and scientists divided by total employment), advertising intensity, and seller market concentration. Buyer market concentration is measured as the sales-weighted average of the four-firm concentration ratios of the industries the seller industry is supplying to. Farber's estimation results indicate that both buyer and seller market concentration have a strong and significant negative effect on the seller industry's R&D efforts. The interaction between these two variables, however, is positive and highly significant. Taken together, these results indicate that the sellers' R&D activity increases with buyer market concentration when the seller market itself is concentrated, but that it decreases with buyer concentration when the seller market is fragmented.

In the following section, I summarize the existing and new theoretical arguments that would lead us to conjecture that vertical organization (a particular combination of supplier and buyer market structures) and technology flows would have a bearing on R&D incentives. To focus on the case that will be considered in the empirical part of the paper, I am concentrating on the impact of supplier industry structure and behavior on R&D incentives of a downstream buyer industry.

## 2.2 A Summary of Theoretical Arguments

### Hold-up Problems

Williamson (1975, p. 204) discusses how R&D incentives are affected by hold-up problems, i.e., by dynamic inconsistency and the lack of appropriate commitment mechanisms. Williamson describes conditions under which the burden of conducting R&D may be shifted from small suppliers to large established buyers in the vertical chain, but the logic of his argument can easily be applied to the interaction between large sellers and small buyers. *Market thinness* (high concentration) and barriers to entry in the buyer industry (e.g. created by first-mover advantages), according to Williamson, limits the rents that an upstream innovator can obtain from selling its technology to downstream firms. Innovation may have the character of a relationship-specific investment, inviting the downstream firm to behave opportunistically ex post. The lack of innovation incentives may then lead to a shift of R&D efforts in the vertical chain. Williamson's comments are explicitly based on the notion that the same R&D projects can be alternatively undertaken by either the supplier or the buyer. In his work, the incentive shift arises from the large firm's problem to commit itself to pay a *reasonable* price for the innovation. Note that in this case, the party which could behave opportunistically ex post will have to undertake innovation because it was not able to commit itself. Williamson implicitly suggests that it would be to the advantage of the downstream firms to commit itself. In that case, no incentive shift would occur in his model.

PRICE DISCRIMINATION

As discussed above, Farber (1981) has suggested that oligopolistic suppliers have comparatively greater power of price discrimination if they face a fragmented buyer industry. He concludes that price discrimination should allow innovators in the supply sector to reap greater quasi-rents for their innovations, and thus promote upstream R&D incentives. Farber's argument is essentially an application of the countervailing power hypothesis to R&D incentives.[6] Since greater appropriability via price discrimination affects R&D expenditures in a positive way, Farber tests his suggestion using upstream R&D intensity as the dependent variable, and finds the expected result confirmed in a cross-sectional regression study.

Farber does not comment on the effect that upstream price discrimination might have on innovative activity in downstream sectors. Whether such an effect should exist or not depends on how price discrimination is implemented in particular pricing strategies. Ideally, the upstream producers would like to leave downstream incentives for R&D intact, since downstream R&D may impose a positive externality on the upstream sector.[7] Extraction of quasi-rents then has no effect on R&D expenditures, sales, and the ratio of these two, R&D intensity.

But even if downstream R&D incentives are distorted, this effect in all likelihood is not visible in the downstream industry's R&D intensity. If upstream suppliers can discriminate and ask some buyer for higher prices than they would be paying under a linear pricing schedule, production costs will be higher for these firms. Theoretical models suggest that a higher level of downstream production costs reduces downstream R&D incentives.[8] However, higher input prices will also depress sales, so that R&D intensity (defined as R&D expenditures over sales) does not necessarily change or only through a second-order effect with ambiguous direction.[9] This is of course one of the

6 This hypothesis originated with Galbraith (1952).

7 This is the classical vertical restraint problem. Under ideal circumstances, the upstream producer would want to appropriate the full downstream surplus and not affect downstream incentives for cost reduction in a negative way.

8 For example, the Dasgupta-Stiglitz (1980) model predicts that R&D expenditures will decrease with higher cost. The Dorfman-Steiner model makes a similar prediction. However, high input costs may induce R&D with the purpose of substitution in which case this relationship may no longer hold.

9 For example, in the Dasgupta-Stiglitz model or in Tandon's (1984) model of R&D, factor prices do not affect the industry's R&D intensity. Note that this statement will not

virtues of this measure, and a reason why it has been so popular in empirical analyses.

Upstream price discrimination *per se* is therefore unlikely to affect downstream *R&D intensity*. This result does not imply that there cannot be a socially detrimental disincentive effect. Clearly, both downstream industry output and R&D expenditures may be reduced in the presence of effective price discrimination by suppliers. Upstream appropriability may actually be too strong even from the supplier firms' point of view. The optimal pricing policy of a supplier may require a credible commitment to charge a relatively low price in the future. If suppliers do not have the capability to restrict their own future behavior in a credible way, downstream producers may reduce their R&D efforts. As a *consequence* then, the supply sector may have to engage in R&D efforts that compensate for the lessened downstream incentives. This is in essence an extension of Williamson's (1975) argument. Excessive appropriability and commitment problems can shift R&D activities from the downstream to the upstream sector. Furthermore, if upstream R&D then enhances downstream output (even without reducing downstream R&D expenditures), downstream R&D intensity is lowered.

### Strategic Supplier R&D

Vertical organization may also have an impact on R&D incentives even in the absence of hold-up and price discrimination effects. In particular, even if the market for disembodied information fails to work properly (as is widely alleged in the innovation literature), supplier firms may profit under certain circumstances from strategically generating information spillovers. In all likelihood, these would not be captured in the technology flow data described above since the latter focus on R&D embodied in products. In the following paragraphs I briefly summarize the theoretical arguments which support this view. A formal model is presented in Harhoff (1996) where I also discuss a number of case studies that have lent considerable support to the hypothesis of strategic supplier R&D.

In intermediate goods markets, oligopolistic suppliers may care more about the overall size of their market than would competitive suppliers under otherwise comparable circumstances. Enlarging the market size can yield quasi-rents even if prices for the suppliers' products cannot be raised, or if upstream competitors have relatively stable market shares. To focus on these incentives, let me assume in the following discussion that the pre- and post-innovation prices for the factor supplied by the upstream sector are indeed identical.

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hold if innovation is factor-biased or if the cost curve is not isoelastic in R&D. However, the effect on R&D intensity will still be of second order.

Upstream producers may then decide to engage in activities that stimulate factor demand or prevent a restriction of demand growth. This may happen in at least three different and conceptually distinct ways.

First, suppliers may seek to induce entry into their buyer industries (*entry effect*). The desirability of the entry effect is contingent on the implications of entry for downstream R&D incentives and factor demand. This strategy may be profitable for suppliers even if downstream R&D incentives are reduced, since firms in the upstream sector may value downstream competition more than downstream innovation. Entry accomodation can occur if the supplier undertakes R&D and offers new entrants the results of its efforts as a costless service. Downstream firms will see a reduction in their own R&D incentives unless they have some form of comparative advantage in R&D.

Second, upstream producers may seek to lower downstream costs or enhance downstream product quality if their customers are not sufficiently engaged in these activities (*productivity effect*). This effect may occur even if the number of downstream firms is fixed and cannot be influenced. Assume for example that the nature of downstream R&D is such that there are no strong appropriation mechanisms. This would be the case if innovations can be copied easily and quickly by other buyer firms, and if patent protection is weak. In this case, suppliers may have to promote the downstream innovation process to enlarge their markets. This may again occur by giving downstream firms access to the results of their own R&D.

The third effect (*preemption effect*) may induce upstream firms to preempt downstream R&D activities to maintain a largely competitive structure in the downstream market. If the supplier firm develops a technology and maintains control over it, then downstream buyers cannot build dominant market positions that are based on technological superiority. Suppose for example that patent protection in the downstream sector is relatively strong. Then supplier firms would want to avoid the emergence of a patent-based monopoly in that industry and the concomitant problem of double marginalization. A simple way to avoid this problem is to obtain the patent by preemption and to give any interested downstream firm access to the technology.

These three incentives arise only if the welfare of firms in the upstream sector is strongly tied to the extent of competition and innovation in the downstream sector, i.e., if the cost share of upstream producers in downstream production is high and if suppliers can demand a factor price above marginal cost. Since strategically induced changes in the downstream industry may represent a public good for the upstream sector as a whole, these strategic incentives are also likely to vary with the market share that upstream firms hold.

The suppliers' incentives for making strategic R&D investments are also contingent on conditions in the downstream sector. In the case of the entry effect, existing barriers to entry and sunk cost investments in the downstream industry are likely to reduce upstream incentives to engage in accommodation of new entrants.[10]

A similar argument holds in the case of the *productivity effect*. The incentives to induce higher productivity in downstream firms are illustrated in Figure 1. Assume that an upstream supplier can transfer a cost-reducing innovation to downstream firms. Suppose that this innovation cannot be sold profitably in a market, since it essentially consists of disembodied knowledge. This is not an implausible assumption at all – many observers have noted that the market for knowledge is highly imperfect. Furthermore, let the upstream firm's profit be an increasing function of downstream output as one could reasonably expect if the supplier sells some commodity to downstream firms.

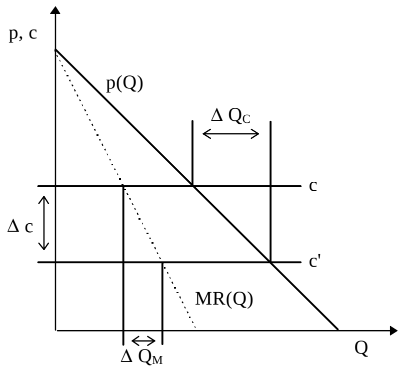


Figure 1: Output Effect of a Cost-Reducing Innovation

The innovation reduces downstream costs from the ex ante level $c$ to the ex post level $c'$ so that $Dc = c - c'$. Consider first the case of a downstream monopoly or of a dominant firm.[11] The downstream monopolist will be able to restrict ex post output and the cost reduction will translate into a relatively small increase in output $DQ_M$. Conversely, in the case of a perfectly competitive downstream industry that adopts the supplier's technology, there will be no restriction on ex post industry output and the supplier enjoys the greatest possible increase in factor demand, denoted $DQ_C$ in Figure 1. Upstream incentives to induce a cost reduction effect are then the stronger, the closer the downstream industry approaches the competitive ideal. In this case, the supplier can shift out the demand curve for his commodity by the maximum possible extent.

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10 The formal argument is stated in Harhoff (1996). Once sunk costs other than those of R&D determine industry structure, the effect of upstream spillover production on downstream industry structure will be smaller, *ceteris paribus*.

11 By output restriction I mean the difference in downstream industry output between i) a perfectly competitive industry in which all firms produce with the low-cost technology and ii) an oligopolistic or monopolistic downstream industry where firms produce less than the competitive output in order to extract rents.

A similar argument can be made in the case of upstream preemption incentives. Preempting downstream innovation is less profitable for suppliers if ex post the downstream industry can still be structured as a tight oligopoly. The reason is again that oligopolists restrict output to assure themselves a price exceeding marginal cost.

Thus, all three mechanisms promise greater marginal returns to suppliers, if the upstream industry is concentrated and the downstream sector is fragmented. This is the type of vertical organization where we are likely to observe a reduction in downstream R&D incentives.[12]

## 2.3 Hypotheses

This section summarizes the above arguments in the form of hypotheses that will guide the empirical analysis. First, we expect that certain types of vertical organization, in particular the combination of a fragmented downstream market with a concentrated supply sector, may lead to a shift of the locus of R&D to the upstream industry, at least with respect to the production of disembodied information. As I have argued above, this should lead to a reduction in the downstream industry's R&D incentives. Thus, we have

> **Hypothesis 1**
> *The research intensity of a fragmented buyer industry is negatively correlated with the industry's dependence on concentrated supply sectors.*

Of course, this hypothesis can also be supported by the arguments put forth by Williamson (1975) and Farber (1981). A strict separation of these hypotheses is not possible. However, Williamson's work suggests that a shift in the locus of R&D also leads to substitution effects with respect to embodied technology flows. Thus, the following hypothesis on the impact of technology flows states

> **Hypothesis 2**
> *Technology flows into a fragmented buyer industry are negatively correlated with the industry's R&D intensity.*

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12 Note that the spillover studies by Bernstein (1988, 1989) and Bernstein and Nadiri (1988, 1989) also show that vertical spillovers lead to a reduction of the recipient industry's R&D expenditures. However, these authors assume that the impact of disembodied information flows is an unintended one. Contrary to this position, the arguments provided here state that suppliers may use spillovers strategically if vertical organization assumes a particular form.

Moreover, these flows should be particularly strong if a fragmented buyer industry faces a concentrated supply sector. Whether the technology flow variables and the structural variables measuring supply sector organization do indeed measure the same or a similar phenomenon should be visible in their performance in a regression analysis. The inclusion of the technology flow variable should weaken the coefficient of the structural measures if such an overlap exists, but it should leave the coefficient unaffected (or strengthen it) if the two variables capture different phenomena.

Note that the hypotheses have not been formulated as causal statements, since a cross-sectional test cannot demonstrate any causal direction. Therefore, statistical support for these hypotheses may be interpreted in various ways. However, since our knowledge of the relationship between vertical organization and R&D incentives is still poor, even these partial correlations should prove instructive.

## 3 Data Sources and Specification

### 3.1 Data Sources

The data used here are taken from the 1976 FTC Line of Business Database and from the 1977 input-output tables of the US economy. The technology flow variables are based on Scherer's (1984) study. The patent data were also compiled by Scherer, and a description of these data is given in Scherer (1983). I also make use of survey data which are often referred to as the Yale survey and described in Levin et al. (1987). To identify these survey variables in the subsequent discussion, I will use the superscript character 'Y', for Yale survey. A summary of variables and data sources is provided in the Appendix (Table A.1). Sample statistics of the dependent and independent variables are summarized in the Appendix (Table A.2).

Combining data from several sources in a test of this form is not without problems. While the Yale survey was designed to be used in conjunction with the FTC data, I had to match the input-output (SIC classifications) to the corresponding FTC data. Such a matching procedure is common practice in cross-sectional analyses of R&D intensity, but it may nonetheless introduce an errors-in-variables problem.

### 3.2 Empirical Specification

While structural models are in principle preferable to reduced-form equations (see Harhoff 1997), they may also impose undue constraints on the estimation results (Cohen and Levin 1989, p. 1085). Since this research is largely exploratory, I model an industry's R&D intensity (denoted RS below) as a linear function of dependent variables. Only company-financed R&D is included in the R&D variable, since the incentives and opportunities to perform government-funded R&D or other contracted R&D work pose a problem in their own right.[13]

Following Cohen and Levinthal (1989), I approximate the right-hand side of the regression equation as a linear function of independent variables. The independent variables fall into four broad categories. A short summary is presented here, and exact definitions are provided in the Appendix. The first three categories (demand, appropriability, and technological opportunity) follow closely the variable definitions used in a recent empirical investigation by Cohen and Levinthal (1989).[14] However, the present analysis is somewhat more limited in degrees of freedom, since I only use the FTC data aggregated by line of business, while Cohen and Levinthal employed the same dataset at the firm level. The fourth group of explanatory variables captures the effect of vertical organization on R&D intensity.

Demand conditions are controlled for by measures of price elasticity (PELAS), income elasticity (INCELAS) and an industry growth rate (GROWTH). These measures were calculated from the 1970 and 1977 input-output tables by Levin (1981). While industry growth and income elasticity should affect research intensity positively, the sign of the coefficient of price elasticity is ambiguous. An aggregate measure of appropriability ($APPR^{Y}$) and imitation lag time for a product innovation ($IMLAG^{Y}$) are also included among the independent variables. These measures are derived from the survey conducted by Levin et al. (1987). I have to assume here that appropriability conditions have remained fairly stable between 1976 and 1983. This assumption has been made implicitly in a number of studies using the appropriability variables from the Yale survey in conjunction with the Federal Trade Commission's 1976 R&D data (Cohen and Levinthal 1990; Levin and Reiss 1988).

It is also common practice in this literature to use measures of *technological opportunity* to control for inter-industry differences. The measures are supposed to capture the closeness of an industry to the sciences, the contributions of other sectors to technical change in the industry, and the maturity of the industry. The Levin et al. (1987) survey data have become the standard source for these variables, but due to the small sample size of 120 lines of business I can only include a limited number of these. However, since

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13 Again this raises the thorny issue of additional endogenous relationships. If government-funded R&D has side effects (e.g. *spillover effects* from the government funded to the privately funded projects) then private R&D incentives are affected by the extent of contract R&D and vice versa. Levin and Reiss (1984) model government-funded R&D in a simultaneous equations model together with company-financed R&D and advertising. The inclusion of the contract R&D equation does not appear to have a great empirical payoff. See also Lichtenberg (1987, 1988) for studies concerning the effect of government-sponsored R&D on private incentives

14 Some of these measures have also been used by Levin et al. (1985).

previous analyses are available I can aggregate variables, for example by relying on some of the Cohen and Levinthal results.

Greater relevance of the sciences related to an industry's technological base may necessitate the allocation of R&D resources that are not required in an industry, where the underlying scientific and technical relationships are well-established and mature. The existence of science-based knowledge may encourage the building of internal R&D capabilities precisely to absorb and utilize the external knowledge, as Cohen and Levinthal (1989) have suggested. External scientific knowledge may also affect the marginal cost of R&D and thus lead to increased utilization of R&D resources. But the effect of *closeness to sciences* is ambiguous ex ante. Besides having a positive effect on a firm's R&D investment, a greater relevance of the scientific disciplines may also result in new information that serves as a substitute for internally produced knowhow and can thereby cause a reduction in R&D efforts. Cohen and Levinthal (1989) study the relevance of eleven basic and applied scientific disciplines on R&D investments and find that most of them are positively correlated with R&D intensity at the firm level. I define as SCIENCE1$^{Y}$ the average relevance of all disciplines that yielded a positive effect in the Cohen/Levinthal study (i.e., biology, chemistry, mathematics, physics, computer science, materials science, and medical science). SCIENCE2$^{Y}$ is defined as the average relevance of disciplines with a significant negative effect (agricultural science, applied mathematics and operations research, geology, and metallurgy) in the Cohen/Levinthal study. This procedure is admittedly heuristic, but it offers the advantage of economizing on degrees of freedom while maintaining relevant control variables.

Several external sectors may contribute to technical change in an industry. To control for the effect that R&D embodied in capital equipment may have, I follow Cohen and Levinthal and include in the regression analysis a measure of contributions by upstream suppliers of production and research equipment (EQSUP$^{Y}$). As an indicator for downstream contributions originating with users of an industry's output, I include the variable USERS$^{Y}$. As von Hippel (1988) has pointed out, users of a product are in many industries at least a source of innovative ideas, and often even the first to build prototypes of innovative products.

Government agencies, laboratories, and universities may also affect an industry's R&D intensity, since they constitute sources of external knowledge with either complementary or substitute character. The variable used here – GOVUNIV – is the average of GOVTECH$^{Y}$ and UNIVTECH$^{Y}$ as used by Cohen and Levinthal.[15]

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15 These two measures were again derived from the 1983 questionnaire survey conducted by Levin and associates. For details of variable definition see Table A.1 in the Appendix.

Finally, the age of an industry's capital stock may have a significant effect on the extent of R&D efforts in comparison to industry sales (Levin et al. 1985). The FTC data include a measure of an industry's percentage of property, plant, and equipment installed within the five years preceding 1976. This measure (NEWPL10) is included in all of the regressions presented below. Again, consistent with previous results, I expect a positive effect, since the newness of production lines will be positively correlated with innovation activities like *debugging, debottlenecking*, etc.

Testing the hypotheses developed above requires an operationalization of the supply industry's characteristics. The supply sector variables used here only capture the possible influence of intermediate goods producers (components, materials, etc.).[16] A simple measure of supply sector organization is the sum of cost shares of intermediate inputs weighted by the respective supply sector's four-firm concentration ratio (WSH for weighted factor shares).[17] I computed this measure from the 1977 input-output tables and census information on industry structure.[18] Any intermediate inputs that were produced by the industry itself (secondary production) were excluded from these calculations. The reason for this exclusion is that vertical integration into the production of these inputs would of course lower the dependence of the downstream industry on upstream supplies.

The aggregate measure of supply sector organization (WSH) can be an ambiguous characterization of a given industry, since very different supply sector structures can be characterized by the same value of WSH. To circumvent this problem I also constructed a second measure that groups supply sectors into two categories according to their four-firm concentration ratio. Supply sector organization is characterized by the cost share of intermediate inputs supplied by industries with a four-firm concentration ratio of greater than forty-five per cent (SH45).[19]

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16 The Levin et al. (1985) survey also measures the contributions of materials suppliers. None of the regression results include this variable, since it had a very small and insignificant coefficient in all specifications. The results also did not indicate any tradeoff between the materials supplier and vertical organization variables.

17 The underlying assumption is here that upstream contributions can be additive.

18 These calculations are based on Miller and Blair (1985, ch. 5). Only the supply of intermediate inputs is captured in the supply sector measures. Capital goods were excluded, since it is virtually impossible to obtain reasonably precise measures of capital goods flows from standard IO tables. The BEA data from which such variables could be constructed were not available for this analysis. For details on the use of the BEA capital goods flow data, see Scherer (1984, p. 430).

19 Initially, I classified upstream industries according to their four-firm concentration ratio into intervals from 0 to 15, 15 to 30, 30 to 45, and 45 to 60, and greater than 60 per cent. Since the inclusion of five variables (plus five interaction effects) would reduce the degrees of freedom considerably, I aggregate the first three groups (supply industries with a four-firm concentration ratio of less than 45 per cent) and the last two (supply

Finally, I use technology flow measures based on Scherer's (1984) study in which he linked R&D expenditures to patents and determined the industry in which the respective technology was applied. From his data I computed a measure of the amount of R&D flowing into an industry from external sources, defined as the difference between the total R&D used by the industry (RDUSE) minus the amount of own R&D spent on process innovations. This indicator is divided by the receiving industry's sales in order to construct a measure analogous to the R&D intensity of the industry. Since Scherer computed the matrix both under a public goods and a private goods assumption, I use both technology flow measures (EXTERN1 for the public goods assumption, EXTERN2 in the case of the private goods assumption) to test the robustness of the empirical results.

The regressions include the measures of supply sector organization and interaction terms necessary to identify relevant subsamples in which a substitution effect between upstream and downstream R&D is either likely or not likely to occur. Since these interaction terms utilize the four-firm concentration ratio (which is presumably endogenously determined with the dependent variable), they are conceivably correlated with the error terms of the R&D regressions. To avoid simultaneity bias I re-estimate the R&D equation using nonlinear instrumental variables (IV) estimators.

## 4 Estimation Results

The results of the regressions following the simple linear model are presented in Tables 1 and 2. Table 1 presents least squares results, while Table 2 compares the OLS estimate for the full model to nonlinear 2SLS estimates.

The heteroskedasticity-robust variance-covariance estimator proposed by White (1980) is used in all regressions, since Breusch-Pagan tests on the benchmark specification (R1) indicate the presence of heteroskedasticity. Heteroskedasticity-corrected OLS results are denoted by OLS-H, while the nonlinear instrumental variables estimators (also using the White correction) are denoted 2SLS. The sample consists of 120 lines of business for each specification.

Since both supply sector variables WSH10 and SH45 produced very similar results, I present only estimates using the SH45 measure. Presumably due to the small sample size,

industries with a four-firm concentration ratio equal to or greater than 45 per cent (SH45)). This cut-off point was chosen in order to minimize the effect of errors in variables, since the variable values in the fifth category were small in most industries. However, the regression results do not change qualitatively if, instead of SH45, the cost share of intermediate goods supplied by industries with concentration greater than sixty per cent is used.

some coefficients have fairly large standard errors, but most results appear to be consistent with those obtained by Cohen and Levinthal. The coefficients on price and income elasticity (PELAS and INCELAS) are highly significant in the OLS specifications and have the same sign as in the Cohen/Levinthal study. The coefficients for GROWTH and $APPR^Y$ are positive, but insignificant in all specifications. They are therefore not reported in the two tables. This result is not completely unexpected for the appropriability variable $APPR^Y$. Statistical shortcomings of this variable have been discussed before and may be due to problems in the survey instrument used by Levin et al.[20] The imitation lag variable ($IMLAG^Y$) only becomes significant after the supply sector and technology flow variables are included among the independent variables.

The point estimates for the two variables measuring the relevance of scientific disciplines also carry the expected sign. Both $SCIENCE1^Y$ and $SCIENCE2^Y$ appear to have strong effects on R&D intensity. But only the $SCIENCE2^Y$ variable is significant throughout all specifications, while the effect of $SCIENCE1^Y$ is weakened once the supply sector and technology flow variables are included. Nonetheless, the separation of the two science variables according to prior regression results has a clear payoff here, since the control for the effect of scientific disciplines is far better than with inclusion of only one aggregate variable (not reported separately).

Greater contributions by equipment suppliers ($EQSUP^Y$) tend to reduce an industry's R&D intensity. This phenomenon may occur for two reasons.

First, the industry's own R&D efforts may be significantly lower if equipment suppliers offer capital goods that are substitutes for an industry's own R&D efforts.

Second, the contributions by equipment suppliers may simply enhance the productivity of the downstream sector without affecting the buyer firms' R&D decisions, thus leading to higher output at the same level of R&D expenditures. We would then expect to see a reduction in the industry's R&D intensity.

Since the supply sector variables only capture the effect of intermediate input suppliers, but not of capital goods suppliers, it is not surprising that the coefficient on $EQSUP^Y$ does not change dramatically once the variables measuring supply sector structure are included. However, one should expect that the inclusion of technology flow variables (EXTERN1 and EXTERN2) would weaken the equipment supplier variable. This is apparently not the case in the simple specifications without endogeneity correction in Table 1. Since the flow variables are based on patent statistics, it is conceivable that the survey variable $EQSUP^Y$ and the flow measure capture largely independent aspects of technology flows and contributions to technical change.

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20 See Griliches's on the relatively large intra-industry variance in his comment to Levin et al. (1987).

Table 1: R&D Intensity Regressions (Dependent Variable: RS)

| *Variable* | *OLS-H (R1)* | *OLS-H (R2)* | *OLS-H (R3)* | *OLS-H (R4)* | *OLS-H (R5)* |
|---|---|---|---|---|---|
| CONSTANT | –3.512* | –3.750** | –3.174* | –3.154* | –2.440 |
| | (1.853) | (1.858) | (1.723) | (1.733) | (1.606) |
| PELAS | –0.234** | –0.217** | –0.181** | –0.218*** | –0.180** |
| | (0.094) | (0.085) | (0.079) | (0.077) | (0.074) |
| INCELAS | 1.379*** | 1.327*** | 1.366*** | 1.305*** | 1.352*** |
| | (0.031) | (0.296) | (0.296) | (0.296) | (0.267) |
| IMLAG | 0.199 | 0.160 | 0.206 | 0.243** | 0.294** |
| | (0.121) | (0.125) | (0.126) | (0.115) | (0.115) |
| SCIENCE1 | 0.677** | 0.657** | 0.496* | 0.549** | 0.370 |
| | (0.278) | (0.271) | (0.287) | (0.252) | (0.262) |
| SCIENCE2 | –0.568*** | –0.631*** | –0.553*** | –0.640*** | –0.557*** |
| | (0.174) | (0.168) | (0.169) | (0.166) | (0.167) |
| EQSUP | –0.352** | –0.355** | –0.387*** | –0.388*** | –0.417*** |
| | (0.137) | (0.136) | (0.137) | (0.131) | (0.130) |
| USERS | 0.345*** | 0.393*** | 0.426*** | 0.353*** | 0.391*** |
| | (0.130) | (0.142) | (0.145) | (0.131) | (0.133) |
| GOVUNIV | 0.469*** | 0.486*** | 0.478*** | 0.494*** | 0.475*** |
| | (0.163) | (0.158) | (0.156) | (0.151) | (0.144) |
| NEWPL10 | 0.323** | 0.338** | 0.363** | 0.322** | 0.349** |
| | (0.161) | (0.157) | (0.154) | (0.156) | (0.154) |
| C4 | | 0.012* | –0.002 | 0.001 | –0.015 |
| | | (0.006) | (0.010) | (0.007) | (0.010) |
| SH45*C4 | | | 0.068* | | 0.069** |
| | | | (0.037) | | (0.028) |
| SH45 | | | –4.036** | | –4.329*** |
| | | | (1.676) | | (1.367) |
| EXTERN1*C4 | | | | 0.024*** | 0.026*** |
| | | | | (0.008) | (0.008) |
| EXTERN1 | | | | –0.573** | –0.653** |
| | | | | (0.287) | (0.291) |
| N | 120 | 120 | 120 | 120 | 120 |
| S.E.E. | 1.353 | 1.339 | 1.327 | 1.300 | 1.281 |

Note: Standard errors are in brackets below coefficients. The Coefficients for the GROWTH and APPR variables are not included. Both coefficients were positive but insignificant in all specifications.

* significant at the 0.10 level (two-tailed test)
** significant at the 0.05 level (two-tailed test)
*** significant at the 0.01 level (two-tailed test)

The contributions by $USERS^Y$ appear to complement R&D efforts within an industry. The coefficients for this variable are extremely stable and in all specifications significant at the one percent level (two-tailed tests). But this variable may also capture the effect of product differentiation. As Cohen and Levinthal (1989) have pointed out, industries that produce custom-tailored goods are likely to do more R&D in order to produce for relatively specific requirements. External contributions from government laboratories and agencies and from universities are also clearly identified by the regressions. Finally, the percentage of *new* plant, property, and equipment (NEWPL10) is positively correlated with the industry's R&D efforts. These two coefficient signs are expected and also consistent with the Cohen and Levinthal results.

The hypothesis to be tested here concerns the effect of the supply sector and technology flow variables. As predicted, the coefficients of the supply sector and flow variables themselves carry negative signs, while the interaction terms between these variables and the industry's own concentration are always positive.[21] In the simple OLS estimations (e.g. in (R5)) there appears to be no tradeoff between the effects of these two variables. Including both in regression (R5) actually strengthens both estimates. Note also that the concentration variable itself does not appear to play any significant role in these OLS regressions. Nonetheless, the results suggest that industries with high and with low concentration appear to react quite differently to the presence of *strong* supply sectors. In the case of fragmented sectors, the presence of oligopolistic supply sectors is clearly correlated with a reduced R&D intensity.

Similarly, greater inflows of R&D as measured by Scherer's indicator appear to have a negative effect on the R&D intensity of fragmented downstream sectors while the result is reversed for highly concentrated ones. It is noteworthy that in the simple specifications in Table 1, there is apparently no tradeoff between the variable measuring supply sector structure (SH45) and the measure of interindustry technology flows (EXTERN1).

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21 Including one of the supply sector variables (WSH10 or SH45) and one of the technology flow variables (EXTERN1 or EXTERN2) without the respective interaction terms produces only small and insignificant coefficients. These results are not shown in Table 1 and Table 2.

Table 2: R&D Intensity Regressions (Dependent Variable: RS)

| | *OLSH* *(R5)* | *NL2SLS* *(R6)* | *OLSH* *(R7)* | *NL2SLS* *(R8)* |
|---|---|---|---|---|
| CONSTANT | –2.440* | 0.107 | –2.836* | –1.054 |
| | (1.606) | (1.518) | (1.678) | (1.828) |
| PELAS | –0.180** | –0.124 | –0.157** | –0.016 |
| | (0.074) | (0.094) | (0.076) | (0.126) |
| INCELAS | 1.352*** | 1.343*** | 1.366*** | 1.449*** |
| | (0.267) | (0.313) | (0.296) | (0.334) |
| IMLAG | 0.294** | 0.428*** | 0.238** | 0.342** |
| | (0.115) | (0.130) | (0.119) | (0.141) |
| SCIENCE1 | 0.370 | 0.364 | 0.431 | 0.167 |
| | (0.262) | (0.323) | (0.273) | (0.395) |
| SCIENCE2 | –0.557*** | –0.644*** | –0.558*** | –0.590** |
| | (0.167) | (0.193) | (0.168) | (0.226) |
| EQSUP | –0.417** | –0.286* | –0.366*** | –0.265 |
| | (0.130) | (0.161) | (0.132) | (0.184) |
| USERS | 0.391*** | 0.442*** | 0.431*** | 0.525*** |
| | (0.133) | (0.148) | (0.145) | (0.175) |
| GOVUNIV | 0.475*** | 0.189 | 0.444*** | 0.238 |
| | (0.144) | (0.204) | (0.144) | (0.239) |
| NEWPL10 | 0.349** | 0.322* | 0.358** | 0.322* |
| | (0.154) | (0.164) | (0.155) | (0.179) |
| C4 | –0.015 | –0.075*** | –0.015 | –0.075** |
| | (0.010) | (0.023) | (0.011) | (0.028) |
| SH45*C4 | 0.069** | 0.082* | 0.061** | 0.029 |
| | (0.028) | (0.044) | (0.029) | (0.058) |
| SH45 | –4.329*** | –5.613** | –3.673** | –1.633 |
| | (1.367) | (2.332) | (1.437) | (3.437) |
| EXTERN1*C4 | 0.026*** | 0.113** | | |
| | (0.008) | (0.043) | | |
| EXTERN1 | –0.653** | –4.300** | | |
| | (0.291) | (1.896) | | |
| EXTERN2*C4 | | | 0.005** | 0.024** |
| | | | (0.002) | (0.010) |
| EXTERN2 | | | –0.156*** | –0.936** |
| | | | (0.058) | (0.448) |
| N | 120 | 120 | 120 | 120 |
| S.E.E. | 1.281 | 1.650 | 1.322 | 1.687 |
| | | $\chi^2$=10.84 | | $\chi^2$=13.08 |

Notes: Standard errors are in brackets below coefficients. The Coefficients for the GROWTH and APPR variables are not included. Both coefficients were positive but insignificant in all specifications. The $\chi^2$ statistic for the overidentification test is the sample size multiplied by the $R^2$ obtained from regressing the residuals on the instruments (Hausman 1983).

* significant at the 0.10 level (two-tailed test)
** significant at the 0.05 level (two-tailed test)
*** significant at the 0.01 level (two-tailed test)

Comparing the results of specification (R3) in Table 1 to those of (R7) in Table 2, it turns out that including the second technology flow variable (EXTERN2) and the respective interaction term (EXTERN2*C4) weakens the supply sector variable only slightly. Based on these results, one would conclude that the coefficients for the flow variables and the coefficient for the indicator of supply sector structure reflect largely independent phenomena.

These results provide consistent support for the suggestion that vertical organization exerts a strong effect on R&D incentives. One could be concerned, however, that the use of the concentration variable causes a bias, since it may be determined endogenously. Similarly, the inflow of technology (measured by EXTERN1 and EXTERN2) is conceivably determined simultaneously with R&D intensity in the downstream industry. Indeed, the theoretical model developed by Harhoff (1996) predicts a simultaneous determination of upstream and downstream R&D incentives.

The specifications presented in Table 2 address these concerns regarding a possible simultaneity bias. Regressions (R6) and (R8) are based on a nonlinear 2SLS specification. R&D intensity is assumed to be endogenously determined with market structure and technology inflows. The instruments used include all exogenous and predetermined variables, i.e., all independent variables with the exception of the four-firm concentration ratio and the technology flow measures. Furthermore, I followed Farber (1981) and used as instruments measures of minimum efficient scale, capital requirements, and the predetermined value of the concentration ratio in 1972. To identify the technology flows, I also included six industry classification variables (DCHEM, DELEC, DMACH, DINST, DMETAL, DFOOD) as instruments. Identification of the nonlinear model was also facilitated by using nonlinear combinations of the instruments (Hausman 1983). The need to estimate a nonlinear relationship arises, because the endogenously determined variables enter the equation both linearly and in interaction terms.

The results in (R6) can be directly compared to the OLS results in (R5). As one expects, the reduced efficiency of the instrumental variable estimator causes standard errors to be somewhat larger throughout. The interaction terms maintain a positive sign, while the SH45 and EXTERN1 variables again have a negative sign. Apparently, the instrumental variables estimation has the strongest effect on the technology flow coefficients. The coefficients for EXTERN1 and the interaction term in specification (R6) are substantially larger than in the simple least squares model. The overidentification test does not lead to a rejection of this specification since I cannot reject the overidentifying restrictions at the ten percent level. Estimating R&D intensity, industry structure, and technology flows under the private goods assumption (EXTERN1) endogenously supports the conclusions derived from the OLS results.

The endogeneity correction has an interesting effect on the coefficients of some of the control variables. The coefficient of $EQSUP^Y$ (measuring the contributions to downstream innovation made by equipment suppliers) is barely significant in specification (R6) and (R8) and considerably smaller than in the simple least squares estimations. The four-firm concentration ratio becomes significant at the five percent level and is negative in both 2SLS-specifications. Finally, the imitation lag variable is significant at the five percent level in (R6) and (R8) and considerably larger than in the OLS specifications. However, none of these differences between 2SLS and OLS estimates is large enough to reverse any of the conclusions discussed above.

If the flow measures computed under the public goods assumption are used, another interesting result emerges from the 2SLS estimation in (R8). The supply sector variables which are significant in the OLS specification (R7) become insignificant and smaller in size, while the flow variable and its interaction term with industry structure remain significant and are larger than in specification (R7). This result on its own would suggest that the technology flow variable EXTERN2 has a stronger explanatory effect than the measures of supply sector structure. Indeed, regressing EXTERN2 on the structural variable SH45, the interaction term SH45*C4, and industry concentration demonstrates a strong relationship, with SH45 being positive and significant at the five percent level. The interaction term is negative and significant at the ten percent level. This result is puzzling because the EXTERN1 variable shows no apparent tradeoff with the measures of supply sector structure. The observation that the flow measure EXTERN2 reduces the supply sector indicators to insignificance could be explained if the weighting scheme used by Scherer (1984, pp. 432) to derive this variable is correlated with the factor share structure for any given buyer industry. However, one would expect this correlation to show up in specification (R7) as well. A less systematic explanation may come from the observation that the flow measures based on the public goods assumption were only weak predictors of productivity growth (Scherer 1984, p. 449). Since calculating the flow measures under the public goods assumption required a complex set of assumptions, the quality of the EXTERN1 variable may simply be superior to that of the public goods measure EXTERN2.

With the exception of these conflicting findings in equations (R6) and (R8), the results support the first two hypotheses derived above. But given the cross-sectional nature of the sample it is not possible to test whether it is strategic behavior by upstream suppliers or some form of hold-up problem that leads to the pattern revealed by these regression estimates.

## 5 Discussion and Conclusions

Despite its importance, the impact of vertical organization on innovation incentives appears to be poorly understood at this point. This paper provides just a first exploratory study, but two simple stylized facts emerge from the empirical analysis and are consistent with a number of theories. First, once a fragmented buyer industry is dependent on a relatively concentrated supply sector, vertical organization appears to matter considerably. Second, technology flows as captured in Scherer's (1984) data appear to act as substitutes for an industry's own R&D if the industry's concentration is relatively low. Both results are broadly consistent with a number of case studies and with the theoretical arguments described above.

The empirical results are consistent with von Hippel's (1982) suggestion that appropriability and structural conditions in vertically related industries may exert a strong influence on innovation incentives. Von Hippel's hypothesis links these conditions to the likelihood that the upstream or downstream sector becomes the source of innovation. This paper has provided some evidence that the patterns of R&D spending may be affected as well. Both statements are ultimately consistent in that one expects (relatively) greater R&D expenditures to precede a consistently higher likelihood of achieving major innovations.

A number of hypotheses need to be given greater attention in future work, in particular the impact of the appropriability regime on shifts in the locus of R&D (and presumably of innovation). Theoretical models (von Hippel 1982, Harhoff 1996) suggest that weak appropriability in any industry would strengthen innovation incentives in vertically related industries, as long as these can profit sufficiently. Thus, suppliers may be willing to provide their customers with technical information for innovation to compensate for the customers' lower innovation incentives. An analysis of this type was not undertaken here, since the Yale data are not particularly reliable regarding the nature of an industry's appropriability regime. Recently generated data from the Mannheim Innovation Panel (described in Harhoff and Licht 1994) may be better suited for this task, and will be used in future work.

Clearly, the results described here need to be interpreted with some caution, since they come from reduced-form models and cross-sectional data. Further corroboration, based on firm level data and more structured models, is highly desirable. Supplier-buyer relationships have been subject to a great deal of change over the last decade (e.g. in the automotive and semiconductor industries). More research on this issue could provide us with important clues as to the nature and implications of those changes. In addition, it would promote our understanding of innovation activities that are distributed across a number of vertically related players.

## Appendix

Table A.1 Variable Definitions (Data sources are given in parentheses)

| | |
|---|---|
| *RS* | R&D Intensity (defined as company-financed R&D expenditures in 1976 divided by total line of business sales and transfers (FTC)) |
| *APPR* | Appropriability measure (Yale Survey, maximum score of responses to questions IA1 ... IA6 and IB1 ... IB6) |
| *IMLAG* | Imitation lag time for a major patented product innovation (Yale Survey, question IIF1) |
| *INCELAS* | Income Elasticity (Levin 1981). |
| *PELAS* | Price elasticity of demand (Levin 1981) |
| *GROWTH* | Time shift parameter (Levin 1981) |
| *EQSUP* | Contribution to technical change by suppliers of research and production equipment (Yale Survey, average score of responses to question IIIE3 and IIIE4) |
| *USERS* | Contribution to technical change by users of industry output (Yale Survey, question IIIE5) |
| *GOVUNIV* | Contribution to technical change by government agencies/laboratories and university research (Yale Survey, average score of responses to questions IIIE6, IIIE7 and IIIE8) |
| *SCIENCE1* | Relevance of scientific and engineering disciplines to technical change (Yale survey, average score of responses to question IIIAI, items a, b, d, e and question IIIA2, items c-e) |
| *SCIENCE2* | Relevance of of scientific and engineering disciplines to technical change (Yale survey, average score of responses to question IIIAI, item c and question IIIA2, items a, b, and f) |
| *NEWPL10* | Percentage of property, plant, and equipment installed within five years preceding 1976 (FTC) (divided by a factor of 10) |
| *C4* | Four-firm concentration ratio (COM 1977) |
| *WSH10* | Aggregate weighted factor cost share, sum of factor cost shares of intermediate inputs weighted by the respective supply sector's four-firm concentration ratio (IO 1977, COM 1977) (divided by a factor of 10) |
| *SH45* | Factor cost share of intermediate inputs supplied by supply sectors with C4 **45(IO 1977, COM 1977)** |
| *EXTERN1* | Value of R&D (private goods assumption) flowing in from other sectors divided by sales of the receiving industry (Scherer 1984) |
| *EXTERN2* | Value of R&D (public goods assumption) flowing in from other sector divided by sales of the receiving industry (Scherer 1984) |

| | |
|---|---|
| *DCHEM* | Dummy variable for chemical industries |
| *DELEC* | Dummy variable for electrotechnical and electronics industries |
| *DMACH* | Dummy variable for machinery producing industries |
| *DINST* | Dummy variable for instruments producing industries |
| *DMETAL* | Dummy variable for primary and secondary metals industries |
| *DFOOD* | Dummy variable for food industries |

Data Sources

| | |
|---|---|
| FTC | Federal Trade Commission. Annual Line of Business Report. |
| COM 1972 | US Bureau of the Census. 1972 Census of Manufactures. |
| COM 1977 | US Bureau of the Census. 1977 Census of Manufactures. |
| IO 1977 | Input-Output-Tables of the US Economy (1977) |
| Yale Survey | Levin et al. (1987) |

All technology flow variables originate from Scherer's (1983) dataset.

Table A.2 Descriptive Statistics

| *Variable* | *Mean* | *Std. Dev.* | *Minimum* | *Maximum* |
|---|---|---|---|---|
| RS | 1.7765 | 1.7366 | 0.0895 | 8.5105 |
| PELAS | 1.8248 | 1.6969 | 1.0000 | 9.2100 |
| INCELAS | 0.9003 | 0.5387 | 0.0000 | 2.0000 |
| GROWTH | 0.9395 | 0.9810 | –1.7899 | 2.9971 |
| APPR | 6.0143 | 0.5674 | 4.0000 | 7.0000 |
| IMLAG | 3.7945 | 0.9335 | 1.0000 | 6.0000 |
| SCIENCE1 | 3.9950 | 0.5638 | 2.2857 | 5.2857 |
| SCIENCE2 | 3.0946 | 0.7251 | 1.5000 | 6.0000 |
| GOVUNIV | 2.7483 | 0.9197 | 1.0000 | 5.7500 |
| EQSUP | 4.2726 | 0.8394 | 2.0000 | 6.0000 |
| USERS | 4.0279 | 1.0280 | 1.0000 | 7.0000 |
| NEWPL10 | 3.8700 | 0.9347 | 1.5000 | 6.5000 |
| SH45 | 0.1799 | 0.1390 | 0.0036 | 0.6419 |
| WSH10 | 2.3581 | 0.6973 | 0.6288 | 4.5392 |
| C4 | 42.5580 | 19.6620 | 7.0000 | 93.0000 |
| EXTERN1 | 0.6762 | 0.7857 | 0.0132 | 6.9572 |
| EXTERN2 | 3.7845 | 2.9387 | 0.4155 | 18.2230 |

Note: 120 observations for each variable. See the text for an explanation of these variables.

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