Institut für Wirtschaftsforschung Halle
Halle Institute for Economic Research

# The Relationship between Knowledge Intensity and Market Concentration in European Industries: An inverted U-Shape

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February 2008 No. 3

IWH-Diskussionspapiere
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Herausgeber:
INSTITUT FÜR WIRTSCHAFTSFORSCHUNG HALLE – IWH
Prof. Dr. Ulrich Blum (Präsident), Dr. Hubert Gabrisch (Forschungsdirektor)
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## Abstract

This paper is motivated by the European Union strategy to secure competitiveness for Europe in the globalising world by focussing on technological supremacy (the Lisbon-agenda). Parallel to that, the EU Commission is trying to take a more economic approach to competition policy in general and anti-trust policy in particular. Our analysis tries to establish the relationship between increasing knowledge intensity and the resulting market concentration: if the European Union economy is gradually shifting to a pattern of sectoral specialisation that features a bias on knowledge-intensive sectors, then this may well have some influence on market concentration and competition policy would have to adjust not to counterfeit the Lisbon-agenda. Following a review of the available theoretical and empirical literature on the relationship between knowledge intensity and market structure, we use a larger Eurostat-database to test the shape of this relationship. Assuming a causality that runs from knowledge to concentration, we show that the relationship between knowledge intensity and market structures is in fact different for knowledge intensive industries and we establish a non-linear, inverted U-curve shape.



Keywords: market structure, knowledge intensity, competition policy
JEL: L16, L40, O33

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## Zusammenfassung

Diese Arbeit ist motiviert durch die Strategie der Europäischen Union, die Wettbewerbsfähigkeit Europas in der Globalisierung durch eine technologische Vormachtstellung (Lissabon-Agenda), zu sichern. Parallel dazu versucht die EU-Kommission, ihre Wettbewerbspolitik an einem stärker ökonomischen Ansatz zu orientieren, insbesondere auch die Kartellpolitik. Unsere Analyse untersucht die Beziehung zwischen steigender Wissensintensität und der daraus resultierenden Marktkonzentration: Wenn sich die Wirtschaft der Europäischen Union schrittweise in Richtung einer zunehmenden Wissensintensität verschiebt, dann hat dies Einfluss auf die Marktkonzentration. Die Wettbewerbspolitik muß sich dann der Lissabon-Agenda anpassen und darf ihr Ziel nicht konterkarieren. Nach einem Literaturüberblick zur theoretischen und empirischen Beziehung zwischen Wissensintensität und Marktstruktur wird mit Hilfe einer umfangreichen Eurostat-Datenbasis getestet, wie sich die Beziehung darstellt. Unter der Kausalitätsannahme, dass der Grad an Marktkonzentration durch Wissensintensität bestimmt wird, weisen wir eine nichtlineare Beziehung zwischen Wissensintensität und Marktstruktur in Form einer inversen U-Kurve nach.

Schlagworte: Marktstruktur, Wissensintensität, Wettbewerbspolitik
JEL: L16, L40, O33

# The Relationship between Knowledge Intensity and Market Concentration in European Industries: An inverted U-Shape[1]

## 1 Introduction

The EU has opted for developing a competitive advantage based upon technological supremacy in the Lisbon agenda to face the challenges of globalisation. Whilst this implies a transformation into a European knowledge-based economy, the question arises as to what effect this may have on market structures. In line with what the Austrian School suggests, we expect market structures to change with increasing knowledge intensity on the supply-side of the economy (Schumpeter-hypothesis). This may be particularly relevant where R&D and eventually innovations depend on tacit knowledge so that technological advance increasingly requires some form or other of cooperation between firms. Where this cooperation occurs between firms in the same industries, this process may well lead to market concentration as a result of the augmented knowledge intensity of the cooperating firms if the cooperating entities merge (or establish a common development-subsidiary).

As a consequence, the Lisbon agenda of the EU might turn out to necessitate a gradual yet distinct change of paradigm for competition policy, which in fact is already taking place under the heading 'more economic approach', albeit from a different intellectual starting point (see e.g. Gual et al., 2005). In our case, this depends on the balance between concentration effects of increasing knowledge intensity and countervailing effects of patent policy. This economic policy question is but a motivation for the following analysis, testing the relationship between market structures or market concentration and knowledge intensity. *We are particularly interested in whether this relationship is different in especially knowledge-intensive sectors of manufacturing industry from more traditional sectors.*

We want to test this at the most general level, because we are interested in the general relationship between market concentration and knowledge intensity and less so in the particular shape of this relationship in individual industries. Further, we are interested in

1 This report has been prepared for the STREP project "Understanding the Relationship between Knowledge and Competitiveness in the Enlarging EU", financially supported by the EU 6th Framework Programme (contract number CIT5-028519). The authors are solely responsible for the contents, the EU assumes no responsibility for any use that might be made of data appearing in this publication.

the general, time-invariant relationship. In the world of product cycles, we may catch in our empirical analysis industries rather randomly in their individual positions of the cycles. This, however, does not provide a problem for our research question but adds to the heterogeneity of market structures and knowledge intensities necessary for a robust analysis.[2] The analysis develops a descriptive taxonomy along the two dimensions of knowledge intensity and market concentration by use of data from Eurostat at the three digit industrial branch level for manufacturing. This data is then used in a regression analysis to find out which proxies for knowledge intensity are significant determinants of market concentration, what role the patent system plays for concentration, and what shape the relationship between knowledge intensity and market concentration takes for knowledge intensive and for more traditional sectors. We hence test the hypothesis that market structures of particular sectors are determined to some extent and significantly in the statistical sense by sector-specific knowledge intensities. Our macro-focus on industries is well in line with the result from empirical literature that industry-specific determinants of innovative activity may be more important than firm-specific ones (see Cohen and Levin, 1989, pp. 1076-1077 and in particular p. 1088, as well as OECD, 1996 for comprehensive literature reviews).

Whilst our regression analysis, by selecting the dependent variable, implicitly assumes a particular causality, it is unable to test its direction: the available data does not permit a stringent time-series analysis and we hence apply a two-stage least squares estimation of simultaneous equations to account for endogeneity between dependent variable (concentration) and determinant variable (knowledge intensity). Also in terms of methodology, our reverse causality-case needs some explanation about the sources of knowledge intensity in which mechanisms affect knowledge intensity first and foremost and not market structures directly. The literature has come to classify three groups of sources of knowledge intensity: demand, technological opportunity, and appropriability conditions. The demand-pull concept holds that R&D investments increase with the size and growth rate of markets (Schmookler, 1962, 1966) whereas the technological opportunity explanation assumes that industries differ in terms of the intensity of the effect of changes in the underlying scientific and technological knowledge on innovative activity (see e.g. Scherer, 1967, or with reference to closeness to science and extra-industry sources of knowledge in Cohen and Levinthal, 1988). Finally, appropriability conditions, or rather the perceived lack of such with a view on the costs of investment in the generation of new knowledge, are more of a political issue with patent and copy-right law at its centre.

2 In terms of our assumed transition to a knowledge based economy in Europe, we are confronted with faster product life cycles driven by technology, i.e. a shorter periods products remain technologically idle in their maturing phase. This results in increasing knowledge intensity across the board.

## 2 The reverse causality case

In the literature, market structure is typically treated as a result of technological determinants like scale economies, sunk costs, product life cycles, market determinants like the size of markets, and firm-specific determinants like the effectiveness of managerial organisation (including the learning curve) and historical chance (in particular head-starts of dominant players). What the literature does not focus on very much so far is whether market structures may also be determined by the knowledge intensity of the industry servicing the market. This, however, is an important issue which is at the heart of the controversially debated question whether innovative activity is propelled by intense competition (low market concentration) or whether an innovator either needs a monopoly position or will have to be enabled by patent law to achieve a monopolistic advantage over competitors by innovating. The former results from the traditional Industrial Organisation paradigm of a one-way causality in the Structure-Conduct-Performance concept, pioneered by Joe S. Bain (1956). The latter has older roots and is typically discussed in the framework of Schumpeter's concept of 'creative destruction': here, the large body of literature largely focuses on the influence of market structure on innovation, again framed in the traditional Industrial Organisation-paradigm. This is hence treated as an issue of intellectual property rights regimes in general and the ability of an innovator to appropriate the necessary profits to make up for his expenses (sunk costs) for innovation-generating research and development in particular. Many years of empirical testing produced rather ambiguous results with some establishing a positive, some a negative relationship, others establishing a positive one (see Cohen and Levin, 1989, p. 1075 for a literature review). Amongst the most prominent results is that of Scherer (1967), suggesting a non-linear 'inverted-U-shape' relationship between R&D intensity and concentration: R&D intensity first increases with concentration up to a maximum of four-firm concentration between 50 and 55 per cent, and declines with concentration thereafter. More recently, a seminal article by Aghion et al. (2005) positively tested an inverted u-shape relationship between product market competition and innovation for UK industries and proposes a theoretical explanation of the inverted U: focussing on the difference between *pre*-innovation and *post*-innovation rents of incumbent firms, competition can foster innovation amongst current technological leaders whereas the Schumpeterian effect of competition may be dominant amongst laggard firms.

Our matter of interest rather turns around the direction of causality of the Industrial Organisation-interpretation of Schumpeter and asks whether not market structures are a result of innovative activity, or more general of knowledge intensity. This effectively reverses the one-way causality of the Structure-Conduct-Performance concept. Whilst ours is today a rather uncommon approach, a redirection of causality has already been attempted mainly in the 70s and 80s with the SPRU-institute of the University of Sussex probably being the protagonist with the most innovative research in the literature (see e.g. Pavitt, 1984 and Freeman and Soete, 1997 but also Dosi, 1988). This approach has recently gained importance in the innovations and market dynamics literature (see Malerba, 2007) and recognises "that Schumpeter's insights about the role of innovation in determining market structures may be more fundamental than his widely tested hypothesis concerning the feedback from market structure to innovation incentives" (Levin et al., 1985, p. 21). Amongst the more prominent early articles is Phillips (1966) and the intuition behind Phillips' attempt in 1971 termed 'success breeds success', is illustrated on the example of the civilian aircraft industry. More recently, this direction of causality was further tested by Levin (1978 and 1985), Nelson and Winter (1978 and 1982) in a simulation model, and Mansfield (1983) in an empirical study. In a case study by Jewkes, Sawers, and Stillerman (1969), the analysis of 61 innovations highlights that innovation is typically realised through interactions of firms of different sizes and complementary expertise, etc. In a division of labour, firms cooperate or merge, thereby acquiring all specific knowledge necessary to generate and market innovations. The case that innovation requires cooperation of firms within the same industry was assessed in the context of licensing by e.g. Katz and Shapiro, 1985, Shepard, 1987, Farrell and Gallini, 1988. They state that where the kind of knowledge required assumes tacit and private characteristics, it cannot be procured on the market which may eventually produce concentration. In Scherer 1976, this causality is motivated by the "erection of strong patent and know-how barriers" (p. 529) by successfully innovating firms.[3]

Probably the closest to our specific matter of interest is the bounds-approach developed by Sutton which was positively tested by many empirical analyses, albeit only for specific and very narrowly defined industries. His approach uses a game-theoretic modelling framework to show that seller concentration should increase with R&D-intensity in industries characterised by high R&D-efficiency in sales and profit gains, the so-called "high-alpha industries". This, however, only until a certain maximum that effectively serves as an upper bound to seller concentration. Technological and demand related factors lie at the heart of this bound effected by Nash equilibrium on market entry (Sutton, 1998).

Very little empirical research is however available in the literature that tests the relationship between knowledge intensity of markets and market structures or dynamics across a broader range of industries within the context of our assumed direction of causality.[4] This report attempts to contribute to fill this gap by way of empirical analysis of recent

3 To the best of our knowledge, this strand of research did not play a significant role in empirical research thereafter, apart from particular industry-studies. This may mainly be rooted in the dominant interest in academia in the determinants of innovation.

4 Amongst the most recent survey articles is *Malerba* (2007) who focuses on the effects of innovation on market structures and dynamics. We may take from this survey that the empirical proof that knowledge intensity in general is positively associated with concentration is still an unresolved matter. This, of course, next to the gaps hat Malerba explicitly lists to lie in the assessment of demand, the industry's type of knowledge-base, and the role of collaboration in R&D for structures.

data on European manufacturing industries. It is important to bear in mind that our reverse causality-case is more of an issue for general competition policy, not of intellectual property rights regimes only, in as much as policy would have to accept increasing concentration on markets in industries that become increasingly more knowledge intense. As a countervailing effect, the intellectual property regime where patent protection allows innovators to appropriate the costs invested into generating innovations, may serve to reduce concentration: in the absence of protection, investors would have to try to keep secret where possible the knowledge they generated and try to buy out their individual knowledge suppliers. Patents and licenses provide instruments to organise this on the market, albeit involving transaction costs. On the other hand, however, the patent system may also be misused by market participants by erecting barriers to the entry of new competitors (patent blocking) or may generate the adverse effect of stifling innovation by effecting a "dense web of overlapping intellectual property rights that a company must hack its way through in order to actually commercialize new technology" (Shapiro, 2000, p. 119-20).

# 3 Descriptive statistics

In the following, we present descriptive statistics for concentration and knowledge intensities. For market concentration, the Herfindahl-index is probably the best indicator. It is, however, not available for a large number of European countries, or even necessarily comparable across countries due to different methods of calculation. Amongst the alternatives, literature suggests the use of Gini coefficients (see e.g. Slottje, 2002). It originates from the concept of income distribution and is based on the Lorenz Curve which compares the cumulative portion of income earned by the cumulative percentage of the population. The Gini coefficient is not influenced by changes in the size of a population, in our application to differences in the number of firms across industries and countries. Furthermore, in contrast to the Herfindahl-index, the Gini coefficient accounts for the observations at the tail end, not just the dominant observations at the top. Our Gini coefficient measures concentration in a particular industry on numbers of enterprises in the same industry, ranked by firm-size: three-digit NACE-branches of manufacturing industries are classified in five labour size classes: (i) one to nine employees per firm, (ii) 10 to 19 per firm, (iii) 20 to 49 per firm, (iv) 50 to 249 per firm, and (v) 250 or more per firm. The coefficient (*gini_lab*) is calculated according to the formula:

$$gini\_lab = 1 - \sum_{j=1}^{n} (X_j - X_{j-1})(Y_j + Y_{j-1}) \text{, where } X_j = \sum_{k=0}^{j} x_k \text{ and } Y_j = \sum_{k=0}^{j} y_k \text{ .} \qquad (1)$$

$x_k$ denotes the share of enterprises in the five labour size classes ($k = 1,...,5$) and $y_k$ the corresponding share of employees in each class *k*. By definition, $x_0 = 0$ and $y_0 = 0$. The variables in capital letters are cumulative shares. As a measure of concentration, this coefficient can take values from zero (no concentration) to almost one: $\frac{n-1}{n}$ (full concentration). Full concentration is when all units (here: employees) are located in one class of enterprises and an equal distribution of the variable over all groups denotes no concentration. As a source of data that is comparable across European countries, we use Eurostat databases. The data-requirement for our analysis is high: first, we need structural data to calculate our Gini coefficient in a consistent way. Second, in order to control for potential country-differences by way of dummies, we had to restrict the number of countries to prevent country-populations with extremely little data: only countries with more than sixty industries with sufficient information to calculate *gini_labs* were included. This reduced the number of countries to 8, down from 25: France is the country with the largest number of observations with 308 industries included into the analysis, followed by the UK with 159 industries, Germany with 147, Hungary with 116, Romania with 90, Finland with 87, Portugal with 78, and Austria with only 66 industries. 103 three-digit manufacturing industries were considered and data was used from the years between 1995 and 2003. The period covered by the data is clearly insufficient for a time-series analysis and we hence use the data in a cross-sectional set-up, assuming that the structure between knowledge intensity and concentration will not have changed between 1995 and 2003. Deducting missing values, this provided us with a total of 1051 cases in an unbalanced, cross-sectional sample. This significant number of cases allows us to conduct meaningful statistical and econometric analyses. The German sample uses the Herfindahl-index, here the number of cases is much lower with 327 cases. In the interpretation of results, we treat our analysis of Germany by use of the Herfindahl-Index as a test of the quality of our *gini_lab* indicator.

Knowledge intensities are proxied as is common in the literature by expenditure for R&D per turnover (*exprd*) and the share of labour employed for R&D (*labrd*). Finally, we devise an interaction term between *exprd* and *labrd* to identify those industries that simultaneously intensively spend on R&D and employ labour for R&D (*knowl*).[5] To improve readability in the presentation of the data, we grouped industries into classes with homogeneous characteristics that have some relationship with our issues of interest (concentration and knowledge intensity).

## 3.1 The raw data and test of variables

The following descriptive Table 1 on patents per labour, labour employed in R&D activities, and expenditure in R&D is presented in manufacturing classes of the WIFO taxonomy (Peneder, 2002). Here, manufacturing industries are grouped into overlap-free classes with homogeneous characteristics that have some relationship to our issue of interest, i.e. knowledge intensity. This provides us with some indication as to which of the three indicators derived from the literature are statistically close proxies of knowledge intensity. In fact, all indicators exhibit the highest means in industries classified as technology driven, lending some support to our knowledge-intensity indicators.

We may further expect above-average knowledge intensities in capital intensive sectors, as here we can assume complementarity between knowledge intensity and high capital expenditure. Yet, only for the indicator of labour employed in R&D is the class of capital intensive industries ranked second in terms of knowledge intensities: for expenditures in R&D, main manufacturing industries are ranked considerably higher than capital intensive sectors, and this hints to us that our *exprd* indicator may not be sufficiently industry-specific. In particular, we cannot tell from the aggregated data whether R&D expenditure in a particular industry is targeted at this very industry or whether this rather takes the form of R&D services by way of outsourcing.

5 Whilst this interaction terms may seem at first sight rather futile, as *labrd* and *exprd* will be highly correlated, each of the two individually is riddled with particular problems: explicit R&D spending may be difficult to measure in some industries whereas in others, employment for R&D only may be a difficult category. An interaction term hence helps to even out those industry-specific difficulties: fulfilling both criteria at the same time is the stricter version of a proxy and reflects the complementary character of expenditure and personnel.

All those stylised facts are somewhat weak, due to the fact that the numbers of observation are sometimes quite low, and variances in the distributions of indices frequently quite high (assuming a level of standard deviation per mean below one would signify sufficiently low variance). A comparison of minimum and maximum levels and the means show that the distributions are typically skewed with a bias to the left and a long tail to the right.

Table 1:
Descriptive statistics for *knowledge intensity* indicators in classes of manufacturing

| *labrd* in % | N | Min | Max | Mean | Standard dev / mean |
|---|---|---|---|---|---|
| Capital intensive | 87 | 0 | 10.118 | 2.027 | 1.086 |
| Labour intensive | 253 | 0 | 7.431 | 0.712 | 2.016 |
| Marketing driven industries | 252 | 0 | 9.278 | 0.718 | 1.888 |
| Main manufacturing | 304 | 0 | 42.076 | 1.558 | 1.850 |
| Technology driven industries | 155 | 0 | 27.068 | 6.511 | 0.840 |
| *exprd* in % | | | | | |
| Capital intensive | 87 | 0 | 4.757 | 0.700 | 1.384 |
| Labour intensive | 253 | 0 | 4.359 | 0.389 | 2.139 |
| Marketing driven industries | 252 | 0 | 8.108 | 0.319 | 2.471 |
| Main manufacturing | 304 | 0 | 25.126 | 0.868 | 2.427 |
| Technology driven industries | 155 | 0 | 15.797 | 3.232 | 0.980 |
| *knowl* in % | | | | | |
| Capital intensive | 87 | 0 | 0.481 | 0.034 | 2.565 |
| Labour intensive | 253 | 0 | 0.309 | 0.014 | 3.630 |
| Marketing driven industries | 252 | 0 | 0.576 | 0.011 | 4.727 |
| Main manufacturing | 304 | 0 | 9.715 | 0.068 | 8.971 |
| Technology driven industries | 155 | 0 | 4.276 | 0.365 | 1.588 |

Source: Raw data from Eurostat, own calculations, classification by use of Peneder 2002.

The following Tables 2 and 3 provide a picture of levels of concentration in the five classes of manufacturing. The first table refers to the data we use in our main part of the analysis and the second table mirrors these descriptive statistics by use of German data. Here, we can consistently use a Herfindahl-index and compare the results with our own indicator for market-concentration. In a first view on the tables, the descriptive analysis already suggests that particularly knowledge-intensive sectors of manufacturing industry, here classified as technology-driven industries, appear to have a higher mean value of market concentration. This applies to the European data, proxied by our *gini_lab* coefficient, and is particularly obvious for the Herfindahl-indices for Germany.

Table 2:
Descriptive statistics for the *concentration* indicator in classes of European manufacturing

| *gini_lab* | N | Min | Max | Mean | Standard dev / mean |
|---|---|---|---|---|---|
| Capital intensive | 318 | 0.000 | 0.908 | 0.699 | 0.304 |
| Labour intensive | 907 | 0.000 | 0.931 | 0.612 | 0.303 |
| Marketing driven industries | 875 | 0.000 | 0.945 | 0.653 | 0.301 |
| Main manufacturing | 993 | 0.000 | 0.945 | 0.702 | 0.232 |
| Technology driven industries | 441 | 0.000 | 0.944 | 0.729 | 0.259 |

Source: Raw data from Eurostat, own calculations, classification by use of Peneder 2002.

Table 3:
Descriptive statistics for the *concentration* indicator in classes of German manufacturing

| *HHI(4)* | N | Min | Max | Mean | Standard dev / mean |
|---|---|---|---|---|---|
| Capital intensive | 121 | 20.040 | 553.04 | 154.52 | 0.624 |
| Labour intensive | 215 | 3.870 | 311.55 | 59.16 | 1.075 |
| Marketing driven industries | 269 | 4.526 | 557.15 | 94.68 | 1.052 |
| Main manufacturing | 320 | 7.715 | 650.17 | 94.76 | 1.247 |
| Technology driven industries | 88 | 11.560 | 477.25 | 160.61 | 0.792 |

Source: Monopolkommission, own calculations, classification by use of Peneder 2002.

Capital intensive industries also show a rather high concentration level which may be rooted in large capital-related fixed costs and entry and exit barriers. Further, we would expect labour intensive industries to have comparatively lower concentration and this is well reflected by our data in both table. In particular for the European data, these results appear to be robust with a high number of observations and a low variance in the distribution of indices.[6] Finally, these results suggest that our *gini_lab* indicator appears to roughly produce the same results as the more precise Herfindahl indicator: rankings between the two indicators only differ between capital intensive sectors and main manufacturing but remain consistent for all other groups. This lends support to our own indicator and we may hence focus our following analysis on the *gini_lab* indicator.

## 3.2 The taxonomy of knowledge intensity and market concentration

Whilst the descriptive statistics of the raw data already gave some indication that the level of market concentration appears to be higher in groups of industries that are rather knowledge intensive and lower for more traditional industries, the comparison of means

6 The low variances for the *gini_lab* indices in comparison to the ones for the HHI(4) are due to the definition of this coefficient between 0 and 1 and means of higher than 0.6. This means that higher variances are mathematically not possible. The high variance in the German data is due to the fact that the distribution is skewed with a bias to the left and a long tail to the right.

over industry groups is still a quite rough guide. In the following next step, we provide a graphical picture of the relationship between knowledge intensity and market concentration over all industries and countries we were able to collect data for (Figure 1). The figures plot all industries of all countries included in the analysis in a two-dimensional space between *gini_lab* and all our three indicators for knowledge intensity, *exprd*, *labrd*, and *knowl*, in turn.

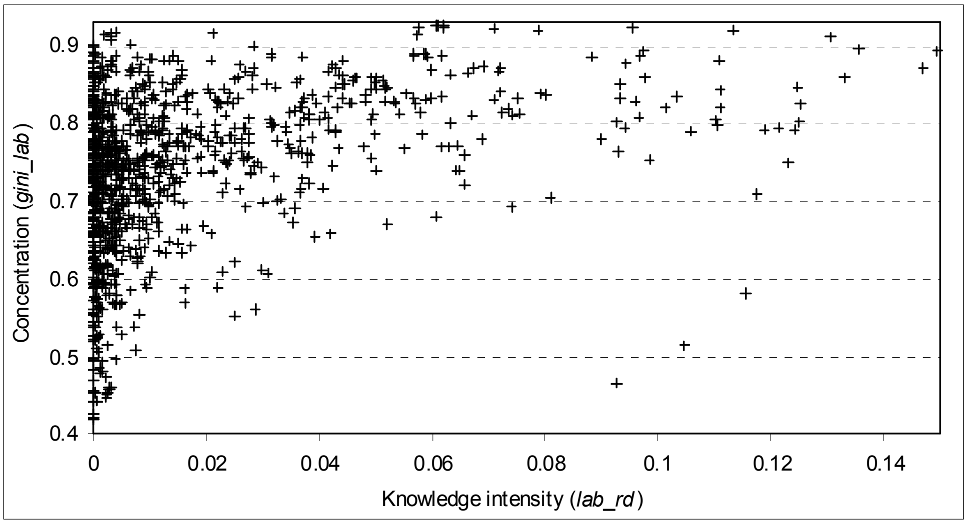
We can hardly detect any clear relationship in any of the three figures. In general, however, we find that knowledge intensive industries tend towards the high-concentration space and rarely appear in the lower part of the figure (low concentration).

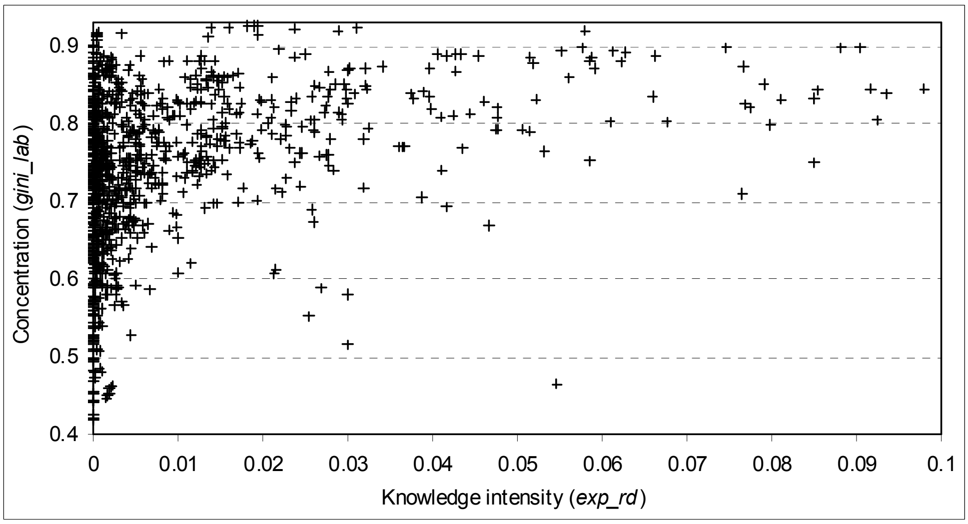
In a further attempt to describe the relationship of our interest, we rank the three-digit industries according to concentration and knowledge intensities to see whether industries ranking high in terms of concentration also rank high with respect to knowledge intensity. First, however, we test whether our three indicators for knowledge intensity offer a roughly consistent industry ranking across countries and time. Here, we report the results of the highest and lowest percentiles: in fact, the food processing, textile manufacturing, manufacturing of wood and wood products, non-metallic mineral products, fabricated metal products, and furniture manufacturing industries ranked consistently in the lowest percentile for all three knowledge intensity-indicators; the highest knowledge-intensive percentile was typically occupied by industries belonging to the manufacturing of chemicals and chemical products, of office machinery and computers, of electrical machinery, of radio, TV, communication equipment, and of medical, precision and optical instruments, as well as watches for all three indicators of knowledge intensity.

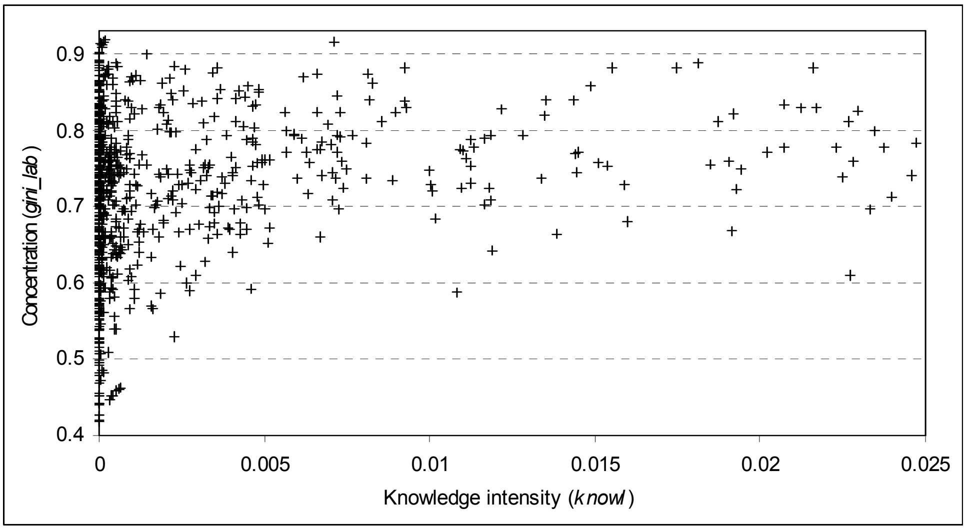
These rankings suggest that our indicators offer a consistent picture across industries and that industry-specifics are more important than country-specific (or time-specific) effects. With respect to concentration, the results are similarly consistent. In the second step, the comparison of industries occupying the highest percentiles for both knowledge and concentration shows strong overlaps: knowledge intensive industries typically rank amongst the highest-concentration percentile and industries with low knowledge intensities rank amongst the lowest concentration percentile. Yet, some important differences emerge: whilst industries like the manufacturing of medical, precision and optical instruments, and watches belong to the knowledge-intensive industries according to our rankings, these industries frequently appear in the low-concentration percentile-ranking. Also, some of the food processing industries appear very low in the concentration ranking whilst at the same time, other food processing industries turn out to be ranked at the highest levels of concentration. All other ranks are occupied by the same industries between knowledge intensity and market concentration. This already suggests to us that there probably is a strong relationship between knowledge and concentration which, however, might not be a linear one at all.

Figure 1:

Taxonomy between knowledge intensity and market concentration




Source: Raw data from Eurostat, own calculations.

To give a picture of what European industries rank highest in both criteria, knowledge and concentration at the same time, we count the frequencies that individual industries appear in the highest percentile in our database over countries and time: the higher the frequency of appearance, the more robust is their characterisation as typically knowledge intensive and at the same time highly concentrated. The five industries with the highest frequency is manufacture of office machinery and computers with 11 occurrences, of domestic appliances (10), of television and radio transmitters and apparatus for line telephony and line telegraphy (9), of electricity distribution and control apparatus (8), and manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations with 7 occurrences.

# 4 Regression analysis

After having reviewed the raw data in a descriptive analysis, we now turn to testing econometrically the principle interest of this paper which is the relationship between knowledge intensity and market concentration. In accordance with our implicit assumption that market structures may be determined by knowledge intensities, we use our concentration coefficients of *gini_lab* for the EU as endogenous variable in our explorative regression models.[7] Following the insights from related empirical research and theoretical discussions on the subject matter, we include industry-specific determinants in our analysis. In line with Scherer's 1967 findings that concentration as determinant of innovation becomes ever more significant as the analysis accounts for industry-characteristics of technology, we control for typical occupational skill levels of employees in the industries by use of dummies for three industry-classes (see also Scott, 1984, where a simple classification of industries into technology groups explains a substantial fraction of variance in R&D intensity). Next, we test for the influence of each industry's extent of vertical integration of production: this reflects the observation that market concentration of an industry may increase in some industries the more its firms integrate vertically (control over up- and downstream markets), whilst vertical integration may in other industries adversely affect economies of scale where firms size becomes a delimiter of efficiency.

Further, we include the degree of closeness or national/regional concentration of individual industries. This tests the hypothesis that intensity of competition increases with import competition (corresponding to a low degree of closeness and a high degree of openness) whilst industries servicing mainly national/regional markets can be assumed to be rather concentrated. Finally, country dummies were included to control for possible country-specific effects. The regression model reads in its theoretical (or rather conceptual) form:

*Concentration = f (knowledge intensity, vertical integration, closeness from external markets (or domestic market share in EU25 market),* $D_{skills}$*,* $D_{countries}$*)*

As proxies for knowledge intensity, the ratio of expenditures in R&D per turnover (*exprd*), labour in R&D per overall labour (*labrd*), and their interaction term (*knowl*) which assumes that expenditures in R&D and labour in R&D are complementary, so that the effect of knowledge intensity on market structures will be particularly strong where both expenditures and personnel in R&D is invested at the same time. These three alternative variables are treated as exogenous in our regression analysis. Vertical integration is measured by the share of each industry's gross value added in the total

7 Here, we do not further consider the German case, because the number of observations are really too low to warrant the use of a regression analysis. The previous analysis, however, may suffice to show that our *gini_lab* indicator may well be used to proxy concentration.

value of production (*verti*). Closeness is proxied by the individual industries' share of domestic turnover in total turnover of the whole region of EU25 (*close*), assuming that the European common market is typically the most important market to engage in for European producers. Further, we test for the influence of the intellectual property right regime by way of patenting intensity of industries. Finally, we control for country-specific and for industry-specific factors by way of dummies. The latter are skill-based dummy variables *skill_bc* (medium skill/blue collar), *skill_wc* (medium skill/white collar) and *skill_high* (high skill) and are calculated by use of the New WIFO taxonomy of Peneder (2002). Because the class of industries with typically low skilled employees is by far the largest, we use this class as reference dummy.

Due to the fact that this regression model is rather explorative in nature, we first test our indicators for possible correlations amongst the explanatory variables and for a first indication of relationship between concentration and our set of indicators for knowledge intensity. The correlation matrix of Table 4 shows that only in the cases between two of our alternative knowledge-indicators *exprd* and *labrd* as well as between them and the amalgamation term of *knowl* produce significant and high correlations. The correlation coefficients all amount to around 0.9, whereas the other significant correlations all remain below 0.4. We can hence assume independence between the alternative independent variables for our regression analysis. With regard to the relationship between our dependent variable *gini_lab* and the proxies for knowledge intensity *exprd*, *labrd*, or *knowl*, we find that correlation coefficients are significant and weak with levels of between 0.25 and 0.35 only. Our proxy for the intellectual property rights regime, *paten*, exhibits a negative correlation with our concentration measure, suggesting that concentration is lower in three-digit industries with a high patent intensity. This results, if it holds in our regression analysis, is not at all counter-intuitive: patents are not only an instrument to protect generated knowledge, but also imply that the new knowledge be published. In particular in narrow or oligopolistic markets, enterprises tend to behave strategically and may prefer to keep their new knowledge undisclosed to competitors.

Lacking a coherent model suggesting a clear one-way causality between market structures (concentration) and knowledge intensity, a regression analysis may be riddled with an endogeneity-problem between the dependant and independant variables. We hence, as a first step, use a two-stage least squares estimation of simultaneous equations.[8] This analysis tells us that an assumed direction of causality of market structures as depending on knowledge intensities can in fact be supported by the data. The other direction of causality treating knowledge intensity as dependent variable, however, could not be confirmed. This allows us to assume that a regression analysis explaining market structures through knowledge intensity has no endogeneity-problem – we proceed with the main

8 The two-stage regression assumes two simultaneous relationships: the relationship treating concentration as depending on knowledge intensity uses vertical integration as its exclusive parameter, the opposite causality is tested with closeness as exclusive parameter.

regression analyses inferring the shape of the above relationship and the influence of other determinants like patents, vertical integration, closeness (or share of domestic market in EU25 markets), industry and country specifics. In the cross-sectional analysis, a set of four regression models are tested. The significance tests are defined at the 5 *per cent* level and we use the original values of our variables (not logs), because we assume an additive relationship between the determinants of market structure.[9] The dependent variable is in fact defined between 0 and 1, i.e. left and right censored, so we first use *tobit*-specifications for our regressions. The results of OLS-regressions, however, are nearly the same, differences emerge only at the 10 *per cent* level for p-values, whereas all coefficients and signs remain unchanged. We hence report the results of OLS-regressions, because here, more regression diagnostics are available to test the robustness of our models.

Table 4:
Correlation Matrix of variables used in the regression analysis

| | *gini_lab* | *exprd* | *labrd* | *knowl* | *paten* | *verti* |
|---|---|---|---|---|---|---|
| *exprd* | 0.3159<br>**(0.000)**<br>1039 | | | - Correlation coefficient<br>- (Significance)<br>- Observations | | |
| *labrd* | 0.3513<br>**(0.000)**<br>1039 | **0.9220**<br>**(0.000)**<br>1039 | | | | |
| *knowl* | 0.2453<br>**(0.000)**<br>1039 | **0.9091**<br>**(0.000)**<br>1039 | **0.8837**<br>**(0.000)**<br>1039 | | | |
| *paten* | -0.1861<br>**(0.000)**<br>320 | 0.0849<br>(0.130)<br>320 | 0.2229<br>**(0.000)**<br>320 | 0.0972<br>(0.083)<br>320 | | |
| *verti* | -0.1945<br>**(0.001)**<br>1037 | 0.0922<br>**(0.003)**<br>1037 | -0.0375<br>(0.228)<br>1037 | 0.0104<br>(0.737)<br>1037 | -0.1453<br>**(0.009)**<br>319 | |
| *close* | 0.1255<br>**(0.001)**<br>730 | 0.3880<br>**(0.000)**<br>730 | 0.3654<br>**(0.000)**<br>730 | 0.2566<br>**(0.000)**<br>730 | -0.0621<br>(0.373)<br>208 | 0.0201<br>(0.587)<br>729 |

Source: Raw data from Eurostat, own calculations.

Model 1 uses *exprd*, Model 2 *labrd*, Model 3 *knowl*. Ideally, all three models should also test for the influence of the intellectual property regime, but because of the low number of observations in patenting intensity of industries, we tested models with and without the variable *paten* and report in Model 4 the results of the model that includes *paten*,

9 A production-function-type of relationship would imply that with any of the independent variables assuming a value of 0, market concentration would also have to be 0 (i.e. no concentration or maximum polypolistic markets). This, however, is rather counter-intuitive, because a market where firms do not engage in R&D at all will not necessarily exist in an atomic market structure.

even if the number of observations drops at an order of magnitude. In order to account for the possibility of non-linear relationships, the regression models were first tested between the dependent variable and increasing powers of our alternative proxies for knowledge intensity without the inclusion of the other independent variables or dummies. This tests for possible non-linear relationships between concentration and knowledge intensity of our three-digit manufacturing industries and is prompted by the assumption in the literature that the neo-Schumpeterian influence of market structures on firms' propensity to innovate may well be of an inverted U-shape. Pioneered by Scherer (1967), this forms part of most empirical work on this topic thereafter (see e.g. Lima, 1999). For *exprd*, *labrd*, and *knowl*, these test regressions establish that adding squared terms increases r-squares without generating new problems. For *paten*, the test for non-linearity does not suggest the use of a squared term. Further non-linearities for the other independent variables are not assumed. The resulting empirical formula hence read:

$$gini\_lab = c + \beta_1 \exp rd + \beta_2 \exp rd^2 + \beta_3 verti + \beta_4 close + \\ + \beta_5 skill\_bc + \beta_6 skill\_wc + \beta_7 skill\_hi + \beta_{8-14} D_{Country} \qquad \text{(Model 1)}$$

$$gini\_lab = c + \beta_1 labrd + \beta_2 labrd^2 + \beta_3 verti + \beta_4 close + \\ + \beta_5 skill\_bc + \beta_6 skill\_wc + \beta_7 skill\_hi + \beta_{8-14} D_{Country} \qquad \text{(Model 2)}$$

$$gini\_lab = c + \beta_1 knowl + \beta_2 knowl^2 + \beta_3 verti + \beta_4 close + \\ + \beta_5 skill\_bc + \beta_6 skill\_wc + \beta_7 skill\_hi + \beta_{8-14} D_{Country} \qquad \text{(Model 3)}$$

$$gini\_lab = c + \beta_1 knowl + \beta_2 knowl^2 + \beta_3 paten + \beta_4 verti + \beta_5 close + \\ + \beta_6 skill\_bc + \beta_7 skill\_wc + \beta_8 skill\_hi + \beta_{9-15} D_{Country} \qquad \text{(Model 4)}$$

In the absence of an explicit structural model describing the general mechanisms determining the relationship between increasing knowledge intensity and market concentration, prior expectations about signs of the specialisation vs diversification and the relative market size variables remain ambiguous, we apply the two-sided test for significance (at the 5 *per cent* level). All models appear to be jointly significant with f-tests exceeding critical values (see Table 5). Model 1, however, fails the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity, hence the use of White's robust standard errors in this model. Further attempts to improve the specification of Model 1 by use of interaction terms did not produce positive results. Model 2 produces slightly higher r-squares and does not appear to have a heteroskedasticity-problem in residuals, yet only considers R&D-labour and neglects the complementary expenditures for R&D. Model 3 uses the interaction term between R&D-labour and R&D-expenses and also passes all tests and

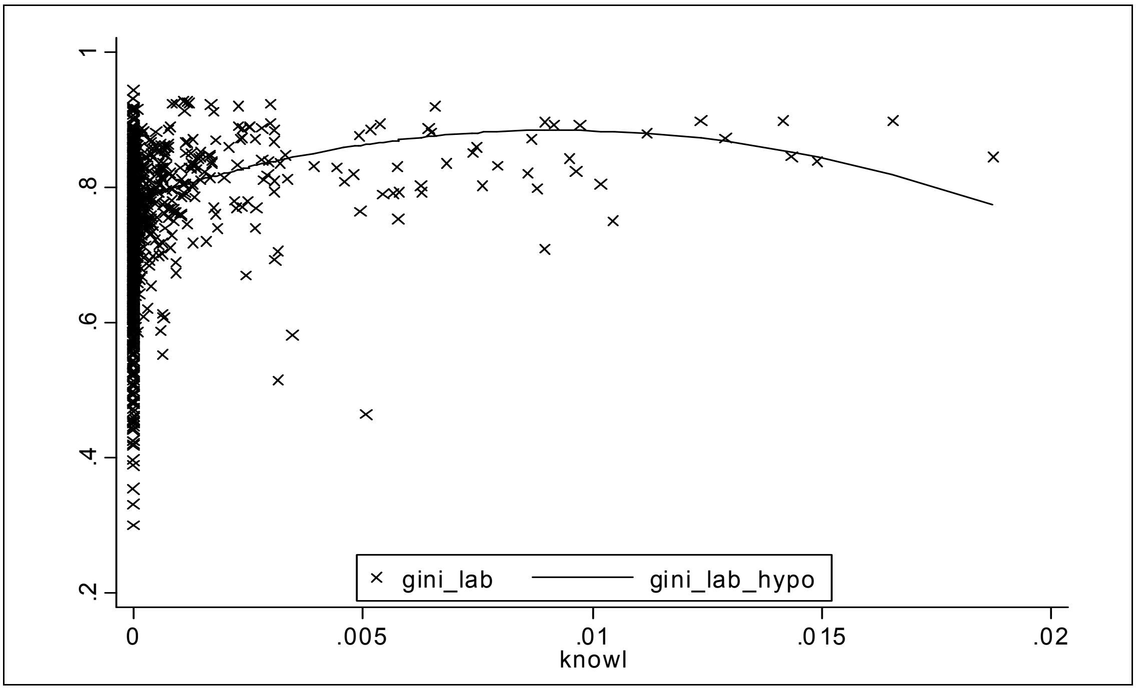
Table 5:
Regression models (dependent variable *gini_lab*)

| | Model 1 | | | Model 2 | | | Model 3 | | | Model 4 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | beta | | P-value | beta | | P-value | beta | | P-value | beta | | P-value |
| *constant* | 0.7705 | ** | 0.000 | 0.7557 | ** | 0.000 | 0.7812 | ** | 0.000 | 0.8931 | ** | 0.000 |
| *exprd* | 4.5023 | ** | 0.000 | - | | - | - | | - | - | | - |
| *exprd*$^2$ | -40.8202 | ** | 0.000 | - | | - | - | | - | - | | - |
| *labrd* | - | | - | 2.5111 | ** | 0.000 | - | | - | - | | - |
| *labrd*$^2$ | - | | - | -12.3074 | ** | 0.000 | - | | - | - | | - |
| *knowl* | - | | - | - | | - | 22.3797 | ** | 0.000 | 13.7048 | * | 0.014 |
| *know*$^2$ | - | | - | - | | - | -1215.168 | ** | 0.003 | 616.9827 | | 0.120 |
| *paten* | - | | - | - | | - | - | | - | -0.5239 | ** | 0.000 |
| *verti* | -0.1771 | ** | 0.000 | -0.1362 | ** | 0.000 | -0.1676 | ** | 0.000 | -0.3910 | ** | 0.000 |
| *close* | 0.1415 | * | 0.030 | 0.1357 | * | 0.035 | 0.1897 | ** | 0.004 | 0.1003 | | 0.280 |
| *D_skill_bc* | -0.0426 | ** | 0.000 | -0.0442 | ** | 0.000 | -0.0435 | ** | 0.000 | dropped | | |
| *D_skill_wc* | 0.0092 | | 0.309 | 0.0016 | | 0.867 | 0.0194 | * | 0.034 | 0.0030 | | 0.773 |
| *D_skill_high* | 0.0098 | | 0.364 | 0.0015 | | 0.892 | 0.0238 | * | 0.027 | dropped | | |
| *D_Austria* | -0.0349 | * | 0.038 | -0.0328 | * | 0.048 | -0.0220 | | 0.198 | 0.0045 | | 0.851 |
| *D_Germany* | -0.0632 | ** | 0.000 | -0.0605 | ** | 0.000 | -0.0666 | ** | 0.000 | -0.0323 | | 0.158 |
| *D_Finland* | -0.0190 | | 0.210 | -0.0157 | | 0.298 | -0.0371 | * | 0.015 | 0.0191 | | 0.423 |
| *D_Hungary* | 0.0256 | | 0.075 | 0.0275 | | 0.052 | 0.0140 | | 0.335 | 0.0115 | | 0.599 |
| *D_Portugal* | -0.0662 | ** | 0.000 | -0.0740 | ** | 0.000 | -0.0835 | ** | 0.000 | -0.0985 | ** | 0.000 |
| *D_Romania* | 0.0741 | ** | 0.000 | 0.0752 | ** | 0.000 | 0.0579 | ** | 0.000 | 0.0445 | | 0.060 |
| *D_UK* | 0.0086 | | 0.474 | 0.0096 | | 0.421 | 0.0020 | | 0.871 | 0.0066 | | 0.697 |
| $R^2$ | 0.3267 | | | 0.3337 | | | 0.2952 | | | 0.3920 | | |
| Adjusted $R^2$ | (0.3135) | | | 0.3207 | | | 0.2814 | | | 0.3510 | | |
| Hettest | Prob > chi2 = 0.0059 | | | Prob > chi2 = 0.0511 | | | Prob > chi2 = 0.0829 | | | Prob > chi2 = 0.6921 | | |
| Observations | 729 | | | 729 | | | 729 | | | 207 | | |

Note: ** denotes significance at 1 per cent level, * at 5 per cent level.

can hence be further interpreted. The inverted U-shape is tested positively[10], i.e. concentration increases with knowledge intensity and at very high levels tends to fall again. The industry branches of the new economy might drive this result: here, competition intensity is quite high with a large number of new firms entering the markets quickly due to low set-up (sunk) costs. At the same time, this industry will report particularly high shares of R&D expenditure and R&D personnel.

Figure 2:
Hypothetical shape of the relationship between knowledge intensity and market concentration




This particular non-linear relationship can furthermore be exhibited by use of a graph (Figure 2): assuming all other determinants of market structure remaining the same (*ceteris paribus*), the relationship between our concentration indicator (*gini_lab*) and our amalgamated proxy for knowledge intensity (*knowl*) is plotted in a two-dimensional diagramme. The marks in the figure represent the original values for our indicators and the line represents the hypothetical values that result from the regression (note that the shape of the lines are strictly hypothetical). Admittedly, the far right hand side of the inverted U-shape is rather weak with only a few observations. Continuously removing observations from the right margin in the regression, however, still produces a significant

10 In fact, the linear version of this regression model also results in a positive and significant coefficient for our knowledge intensity proxies, so that the results of the non-linear models that include the squared term can be interpreted as containing additional and still consistent information.

U-shape in the regression and the slope of the hypothetical curve; we have tested this for a level of 0.001, which clearly excludes observations outside the bulk.

In Model 4, adding our variable for the influence of the intellectual property rights regime exemplarily for our amalgamated knowledge intensity proxy, the number of observations is critically low. Never-the-less, the regression model appears to be consistent with even higher r-squares and no heteroskedasticity-problem. Only four determinants turn out to be significant with *paten* receiving a significant negative sign. Still, this model passes all tests and produces the highest r-squares, albeit not at an order of magnitude. We may conclude from this model that where firms prefer not to use patents, market structures become increasingly concentrated (because of the secrecy-implications). This is in fact in line with the conclusion that "there is even less evidence of a positive relationship between innovative output and market structure" (OECD, 1996, p. 16).

In regard to our testing for the influence of vertical integration and closeness or national/regional market share in EU25 markets, Models 1 through 3 consistently tell us that both determinants are in fact significant and that market concentration tends to fall with increasing levels of vertical integration (proxied by *verti*) and with increasing openness to foreign (European) markets (proxied by *close*): it may not be surprising that industries with high levels of vertical integration will contain firms that are predominantly highly specialised and that these will tend to operate in rather polypolistic markets, each seeking their market share via varieties of niche-products. What is even more, vertical integration reduces the potentials for scale economies, and the traded literature of industrial organisation holds that concentration typically rises with increasing scale economies. The positive relationship between closeness or national/regional market share in EU25 markets and market concentration may also be plausibly motivated by the assumption that industries that operate at the national/regional level have little competition from foreign (EU25) markets.

The regression models additionally control for country and occupational skills effects. Only in Model 3 do skills-dummies turn out to be significant with lower skill-intensities tending to be negatively related to concentration and higher skill-intensities positively. This lends further support to our result that concentration appears to increase with increasing knowledge intensity (that is, if not accounting for very highly knowledge intensive industries). The results for the country-dummies are more frequently significant than not, and typically, Western countries have a negative coefficient whereas Hungary and Romania as our two examples for Eastern post-transition countries have a positive sign. A further test not reported here involving data for our Eastern post-transition countries Romania and Hungary only does not contradict the qualitative results, albeit with frequent insignificancies (and much lower numbers of observation). We hence do not expect that the relationship between knowledge intensity and market concentration is different in post-socialist economies.

# 5 Conclusions

If the results generated in our taxonomy and our regression models are in fact trustworthy, we may conclude that in fact market structures appear to depend on knowledge intensity of the industries involved: concentration appears to rise with increasing knowledge intensity; very high knowledge intensity then appears to relate to moderating levels of concentration (which, however, may be a particular effect rooted in the new economy-phenomenon). We could have controlled for or tested more determinants of market structure, but because the results for determinants that we are mainly interested in, i.e. knowledge intensities, remain robust with or without the inclusion of the determinants and dummies we did add, we can be fairly sure about the final conclusion.

The implications of these results for competition policy raise the question as to how competition policy should treat concentration and cooperation between firms in particularly knowledge-intensive sectors? Or in a more dynamic version: should competition policy try to stem concentration tendencies, if those result from a transition to a higher knowledge intensity of the industry involved? We have learned from a vast body of related research that an industry's technological opportunity is affected by the contribution of technical knowledge from sources external to the industry like suppliers, customers, universities, technical societies, government, and independent inventors (for a review on this literature, see Cohn and Levin, 1989, p. 1088). If hence technological development in general or innovation in particular depend on cooperation between firms via mergers, collaborative R&D and innovation activities, then some concentration will be a good thing and a strict *per-se* legal treatment of competition cases will not allow the economy to reap full benefits from its potentials for technological advance via R&D and innovation.[11]

The novelty of this paper lies in its competition policy motivation of an analysis that has been largely overlooked by the profession. Albeit, with the EU economic area increasingly becoming more knowledge intensive in the process of globalisation, the effects on market structure and concentration become increasingly important for competition policy. This parallels the call for a 'more economic' approach for competition policy. In the latter, the focus is on the determinants of innovation motivated by a more dynamic view of competition as an engine for the efficient allocation of resources. Our analysis and results hence complement this call and lend further support for a more economic approach, albeit from a different intellectual starting point.

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11 On the other side, however, if the rule-of-reason is but an unclear and non-transparent vehicle treating each case according to criteria unknown to the actors at large, then legal uncertainty will perhaps even more prevent technological advance by preventing cooperation that is not only economically but also legally risky. This, however, should be subject to another piece of research.

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