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Technology portfolio and market value[#]

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Abstract

This paper discusses the impact of a firm's technology portfolio on its market value. Two concepts are used to characterize a firm's portfolio: the number of technological fields and the degree of relatedness within the portfolio characterized by the amount of joint occurrences of patents in technological fields. Based on a theoretical framework using an expanded Tobin's q approach, it presents evidence for a negative influence of portfolio size on the market value caused by a diminishing potential to make use of economies of scale. This discount can be counterbalanced when the relevant fields share a common technological base which is measured by the degree of technological relatedness.

Keywords: technological portfolio, relatedness, patent statistics, tobin's q, economies of scope
JEL classification: L25; O31; O32

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I. Introduction

Is a wide research portfolio in line with market value maximization? So far, empirical research has concentrated on evaluating the impact of research and development (R&D) and patents on the market value of a firm. Relatively little is known about the relationship between the composition of the research portfolio and its valuation by financial markets. Efforts in answering this question directly lead to an application of the theory of the multiproduct firm (Panzar and Willig 1977, 1981): economies of scope and scale in future research and production.

In this line of theory, it is widely assumed that economies of scale and scope in R&D reveal a significant impact on a firm's innovative performance (Henderson and Cockburn 1996). Firms acquire a specific knowledge base over time which is used as an input in future research projects. This input is self-generated and cannot be provided efficiently by the market. By taking patents as an approximation of research output as suggested by Pakes (1985), and grouping them into technological fields, we can transfer the idea of the multiproduct firm to the level of technologies. Knowledge serves as a shareable input that is used in research on various technologies. The innovations patented belong to certain fields and provide access to corresponding technologies. All technological fields covered can be summarized by a firm's technology portfolio. We define the technology portfolio by the number of technological fields a firm is engaged in research and the relatedness of these fields within the portfolio.

The technology portfolio can either be highly specialized on certain technologies or rather broad and providing access to many technologies (Leten et al. 2007). Individual characteristics of a firm's technology portfolio determine its potential to make use of economies of scale and scope in the knowledge creation process. The fact that we observe multi-technology firms implies the existence of economies of scope in the knowledge generation process caused by internal knowledge spillovers (Granstrand 1998). In contrast, economies of scale are mainly driven by learning effects due to higher specialization in certain technologies (Garcia-Vega 2006).

In this paper, we focus on the idea that the market values two firms – depending on technology portfolio characteristics – with equivalent tangible and intangible assets differently. Economies of scale and scope in research and development influence the cost structure of a firm and thereby current and expected future cash-flows.

The purpose of this paper is twofold: firstly we analyze the impact of the size of the portfolio on the market value of a firm and secondly provide evidence for the hypothesis that technological relatedness influences the market value via its potential to make use of economies of scope. We test the suggested relationship in an expanded Tobin's q model containing individual heterogeneity. A simple count measure and the number equivalent entropy are used to capture the portfolio size.

The paper is organized as follows: section I summarizes the relevant literature; section II introduces the theoretical framework; section III provides the metrics used to capture technological fields and their relatedness; section IV describes the data sources; section V presents the econometric specification while section VI discusses the results of our model. Finally, section VII summarizes the main conclusions.

II. Theoretical framework

Empirical studies on the relationship between research and development and the market value mainly come to the conclusion that innovative efforts are rewarded by financial markets[1]. Usually, valuation equations based on a firm's assets are used to analyze the aspects of interest. The market value encompasses those assets that influence expected future cash flows and profits (Connolly and Hirschey 1988). Changes in these assets alter the expectations about uncertain future cash flows and hence also the present value of the firm's expected entire stream. The market value under simplifying assumptions should immediately react on this and reflect the revaluation that has taken place. Predominant in the literature is the division of assets in tangible ones like plant, equipment and inventories and intangible assets, which are usually approximated by R&D expenditures, patent counts or patent citations[2].

The technologies generated by the R&D process may influence the market value in two ways: firstly, the current knowledge and technology portfolio serves as an input for future research projects and thereby determines its cost structure. Inputs like researchers, equipment and codified knowledge can be devoted to several technological fields but at varying costs. A widespread technology portfolio may generate economies of scope in research. Future research in many fields will be less costly when the corresponding knowledge base already exists (Teece 1980). In contrast, economies of scale arise due to specialization on certain technologies when firms benefit from learning effects (Fai and von Tunzelmann 2001).

[1] For a detailed survey see Hall (1999).

[2] Examples for the application of various approximations of intangible assets can be found in: Hall et al. (2005), Bloom and van Reenen (2002) and Shane and Klock (1997)

A firm's current technology portfolio is linked to future production technologies that will be used to generate future cash-flows. Hence, the potential for economies of scale and scope on the innovation stage can be taken as a signal for future production.

The main methodology to evaluate impacts on the market value was developed by Griliches (1981) and is based on hedonic Tobin's q equations[3]:

$$V = q[A + \gamma K] \quad (1)$$

In this standard version of the value function, the market value (V) is assumed to equal the weighted sum of physical (A) and intangible knowledge assets (K). The variable q can be interpreted as the current market valuation coefficient of a firm reflecting its monopoly position, differential risk and overall costs of capital adjustment.

We adopt the standard version of the value function and expand it with a term capturing the number of technological fields in the portfolio. Within this framework, the range of activity where a firm can utilize its assets productively and generate future cash flows is denoted by the variable D, which stands for the size of the portfolio meaning the degree of technological diversification. Furthermore, we assume its impact may vary with the technological relatedness (R) of fields within the portfolio. The technological relatedness captures the amount of common knowledge between fields and thereby influences the potential to make use of economies of scope:

$$V = q\left[(A + \gamma K) D^{\theta + \delta R}\right] \quad (2)$$

The term δR adjusts the elasticity of the number of technological fields with respect to the market value by including technological relatedness and its corresponding coefficient delta. Accordingly, the influence of the number of fields is either reduced or enhanced by this modification depending on the expected parameters of the model and the measure of relatedness in use. This discount can be counterbalanced when the relevant fields share a common technological base which is measured by the degree of technological relatedness. Formally speaking[4]:

$$H : \theta < 0 \quad \& \quad \delta > 0 \quad (3)$$

There are mainly three reasons for this hypothesis:

Firstly, a firm reduces its ability to exploit economies of scale when the composition of its portfolio changes. This is linked to the idea of ray-economies of scale developed by Baumol et al (1988). In contrast, the benefits generated by economies of scope depend on the amount

[3] The value function assumes constant returns to scale.
[4] The applied measure of relatedness exhibits an expected value of zero, relatedness matters only when being larger (positive value) or smaller (negative value) than expected.

of relatedness in the portfolio since it will be less costly to develop these technologies with the existing knowledge base. Secondly, Wernerfelt and Montgomery (1988) argue that transferring technological knowledge to new fields might lead to a reduction in economic efficiency since factors of production contain a firm and thereby field specific component[5]. Accordingly, the rent generated by these factors depends on the closeness of the current field and the new ones. Still firms may decide to spread their economic activity because of excess capacity in their R&D department even though they are left with a lower rent generated by their factors of production. Thirdly, the decision to cover many technologies can be interpreted as an indicator for the degree of risk aversion of a firm's decision makers. Future returns of technological improvements being generated by cash flows from future markets are uncertain and working in many fields can reduce the variance of these returns. Accordingly, the negative impact of D on q can be seen as causing a risk premium (Mansi and Reeb 2002).

III. Measurement of technological diversification and relatedness

In order to test our hypothesis suggested above, we need to derive measures to characterize a firm's technology portfolio. In particular, we need a count measure for the portfolio size and an index for the degree of relatedness within the portfolio. We use the technology based USPTO patent classification system to define technological fields.

To capture the number of fields, it is either possible to use an unweighted count measure, which simply sums over the areas of research activity, or to apply a weighting scheme like the one suggested by the number equivalent entropy. Both measures will be tested in the empirical part of this paper. The weights applied in calculating the entropy measure reflect the relative importance of each field (j=1…N); therefore, we employ the share of the patent count S_j dedicated to each field:

$$S_j = \frac{pc_{kj}}{\sum_{l=1}^{N} pc_{kl}} \qquad (5)$$

The weighting scheme mirrors the relative sizes of the technological fields in the firm's patent portfolio. It is obvious, that the entropy measure assigns a lower weight to fields with small shares than the unweighted count measure. The entropy of firm k's portfolio can be derived using the common formula[6]

[5] see also Montgomery and Wernerfelt (1988)

[6] For a first application of the entropy measure in industrial economics see Jacquemin and Berry (1979).

$$E_k = \sum_{j=1}^{N} S_j \ln\left(\frac{1}{S_j}\right) \qquad 0 \le E_k \le \ln(N). \tag{6}$$

In line with our theoretical model, for interpretative purposes we use a number equivalent transformation of the entropy measure to obtain the adjusted number of fields[7], which is constructed by exponentiating E_k:

$$NE_k = e^{\sum_{j=1}^{N} S_j \ln\left(1/S_j\right)} \qquad 1 \le NE_k \le N \tag{7}$$

The number equivalent entropy lies between 1 and 42, which corresponds to the total number of fields in the classification system. Only in case of equal distribution of patents across fields, its value will be equal to the simple field count; otherwise it will be lower. Hence, a firm with a number equivalent entropy of five and actually serving seven fields is as diversified as another firm engaged in five fields and having twenty percent of their patents in each field.

Besides the size of the technology portfolio, the relatedness of the fields within the firm's portfolio matters. The measure of technological relatedness applied here is based on a method developed by Teece et al. (1994), which was used to determine how coherent a companies' product portfolios is. The main assumption is that activities being related are more frequently combined within the same cooperation. Nesta and Saviotti (2005) adapt this approach and conduct a corresponding analysis on the patent class level[8]. Applying this concept to patents implies that patent classes exhibit technological relatedness if patents are more often assigned to the same combination of classes than expected. Instead of using patent classes, we conduct this analysis on the level of technological fields to determine their relatedness within a firms' technology portfolio.

Let K be the total number of patent applications being assigned (to two or more patent classes) and $P_{ik} = 1$ in case that patent k is assigned to field i, and 0 otherwise. The total number of patents assigned to field i equals $C_i = \sum_k P_{ik}$. Using this notation, the number of joint occurrences in fields i and j can be depicted as $J_{ij} = \sum_k P_{ik} P_{jk}$. This count is used to derive our measure of relatedness. Applying it to all possible pairs we obtain a square $(N \times N)$ matrix with typical cell J_{ij}. Since J_{ij} can be effected by either an increase in the relatedness of fields i and j or an increase in the number of patents assigned to i or j, Teece et

[7] The number equivalent interpretation of the entropy was suggested by Baldwin et al. (2001).

[8] A similar approach is used by Piscitello (2000) and Breschi et al. (2003), where the number of firms patenting in two or more fields is used to determine technological relatedness. In contrast, Leten et al. (2007) compare the observed number of co-citations with its expectation.

al. suggest to compare the observed value of J_{ij} with its expectation. The expected value is derived under the hypothesis of joint random occurrences using a hypergeometric distribution[9] for the number of patents x_{ij} assigned to fields *i* and *j* with mean

$$\mu_{ij} = E(X_{ij} = x) = \frac{C_i C_j}{K} \tag{8}$$

and variance

$$\sigma_{ij}^2 = \mu_{ij}\left(\frac{K - C_i}{K}\right)\left(\frac{K - C_j}{K - 1}\right). \tag{9}$$

If the actual number of joint occurrences J_{ij} in fields *i* and *j* exceeds its expected value μ_{ij}, then the two classes are assumed to be related. The measure of relatedness between the two fields is thus derived by

$$t_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}}. \tag{10}$$

A negative value of t_{ij} indicates low relatedness since less joint occurrences are observed than under the hypothesis of randomness. Accordingly, large and positive values of t_{ij} show a high degree of relatedness between the technological fields *i* and *j*.

Calculating the pairwise relatedness measures for every possible combination of fields leads to a symmetric $(N \times N)$ relatedness matrix. This matrix is used to calculate a measure of relatedness of a firm's technology portfolio. The derivation is conducted in two steps: firstly, the weighted-average relatedness WAR_{ki} of field *i* with all other technological fields within firm *k's* portfolio is derived:

$$WAR_{ki} = \frac{\sum_{j \neq i} t_{ij} p_{kj}}{\sum_{j \neq i} p_{kj}}, \tag{11}$$

where p_{kj} denotes the number of patents of firm *k* assigned to field *j*. Obviously, WAR_i depends on the number of fields a firm is engaged in research. Secondly, we aggregate the WAR_{ki}'s on the firm level by weighting them with the same scheme used above to determine the average relatedness of a firm's technology portfolio:

$$TC_k = \frac{\sum_{i=1}^{N} WAR_{ki} \times p_{ki}}{\sum_{i=1}^{N} p_{ki}}. \tag{12}$$

---

[9] K denotes the population, C_i number of successes and C_j the sample size.

A value of TC_k from equation (12) suggests a generally high relatedness or complementarities within the portfolio, while a negative value indicates the opposite. It is worth mentioning in this context that TC_k will vary even when the structure of the technology portfolio remains constant in case the relatedness of the fields t_{ij} change.

IV. Data and Descriptives

The dataset stems from four different sources: the NBER Patent database, the manufacturing sector masterfile by Hall[10], the CUSIP match file and the USPTO patent classification scheme. The NBER Patent database contains all patents granted by the USPTO during the period 1965 to 1996, including citations[11]. We exploit this information to calculate firm specific patent and citation stocks using the perpetual inventory method with a 15% depreciation rate which is common in the literature (Griliches and Mairesse (1984), Hall (1993)). Firm specific data are taken from an updated version of the manufacturing sector master file. The data stem from the Compustat Annual Industrial Files and provide information on market value, book value of physical assets, and R&D investments. Firm specific R&D capital stocks are calculated using the perpetual inventory method again with 15% depreciation. The CUSIP match file provided by the NBER Patent database is used to merge patent and firm data. We add the USPTO patent classification scheme to define technological fields. Every patent applied for at the USPTO must have at least one principal mandatory classification consisting of class and subclass. A class hereby generally delineates one technology from the other, whereas subclasses delineate processes, structural features, and functional features of the subject matter encompassed within the scope of a class. Patents with more than one claim receive additional mandatory classification for all claims disclosed. The USPTO classification systems uniquely identifies more than 500 classes and over 150 000 subclasses. It therefore captures every patented innovation in detail. To identify the technological fields a firm is engaged in research, we aggregate the classification scheme to 42 main groups using the “Classes within the U.S. Classification System” [12] provided by the USPTO[13].

Combining our datasets and dropping all companies with less than two patents in our observation period, we end up with an unbalanced panel of 1700 firms for the years 1969 to

[10] For details on variables and construction, see the documentation by Hall (1990) on the original Manufacturing Sector Master File 1959-1987.
[11] A detailed description is provided in Hall et al. (2001).
[12] Classes within the U.S. classification scheme December 2006.
[13] A table of the 42 groups is provided in appendix 1.

1995. Firms in our sample are publicly traded at the American stock exchange and belong to the U.S. manufacturing sector. The analysis is conducted using a sample from 1983 onwards since several important changes took place in the US legal environment in the early 1980s which enhanced the ability of patent holders to enforce their patents and led to increased patent activities of companies (Kortum and Lerner (1998), Hall and Ziedonis (2001)). Due to data restrictions, mainly because of the NBER CUSIP match file, the sample lasts until 1995.

Table 1 Summary Statistics[14]

Variable	**N**	**Mean**	**Median**	**SD**	**Min**	**Max**
Tobin's q	9584	1,79	1,37	1,34	0,00	8,29
R&D/Assets	9584	0,35	0,171	0,70	0,00	19,45
Patents/R&D	7832	1,01	0,55	5,11	0,00	333,33
Citations/Patents	9553	12,99	10,20	10,09	0,00	179,01
Number eq. Entropy	9584	5,0	3,99	3,72	1,00	20,98
Number of Fields	9584	8,28	5,00	7,97	1,00	39,00
Relatedness	8424	8,87	5,35	13,65	-35,46	108,19

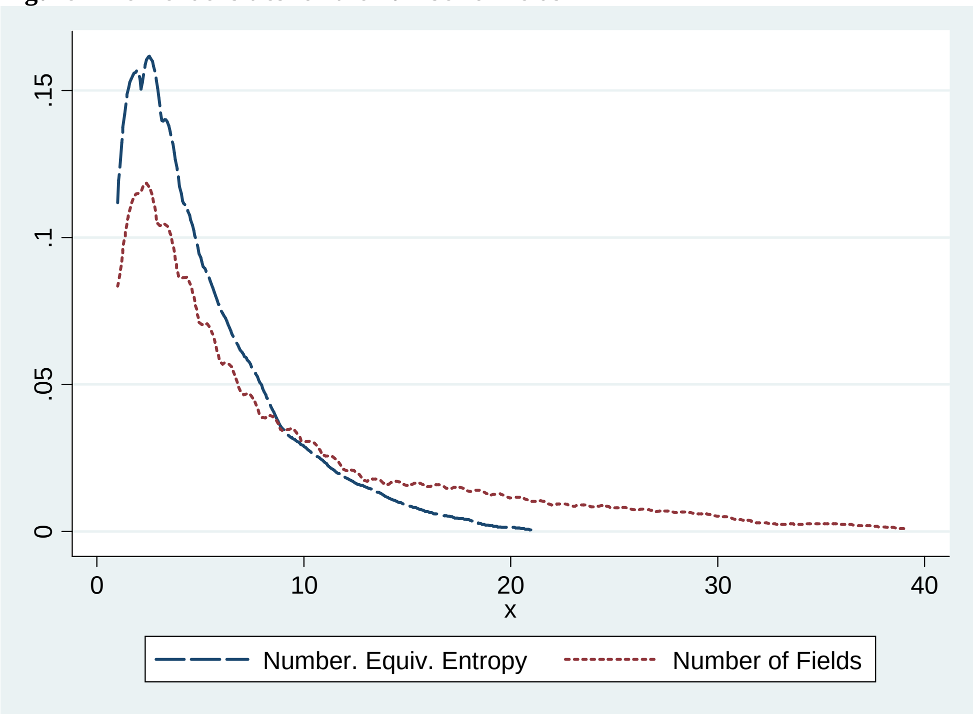
Table 1 displays the sample statistics of the main variables used in our analysis for the estimation period 1983-1995. On average, the market value exceeds the book value by a factor of 1.8. Comparing mean and median of Tobin's q, we observe a distribution skewed to the right. The average value of the R&D/Asset ratio shows that R&D efforts of patenting companies are considerably high compared to their assets.

In our sample, firms are on average engaged in eight technological fields. When a weighting scheme is applied, this number reduces to five fields. None of our companies observed is active in all 42 fields. The maximum portfolio size equals 39 technologies. This number reduces to 20 when the number equivalent entropy is used since some fields are of less importance.

In Figure 1, the kernel densities of the number equivalent entropy and the unweighted count measure are depicted to illustrate their distribution in our sample. We observe that the distribution of the number equivalent entropy is more skewed to the right than the count measure due to different weighting schemes. Most firms cover about 1 to 6 fields within their patent portfolio and the share working in more than ten fields becomes substantially small, especially when we weight the fields according to their relative importance.

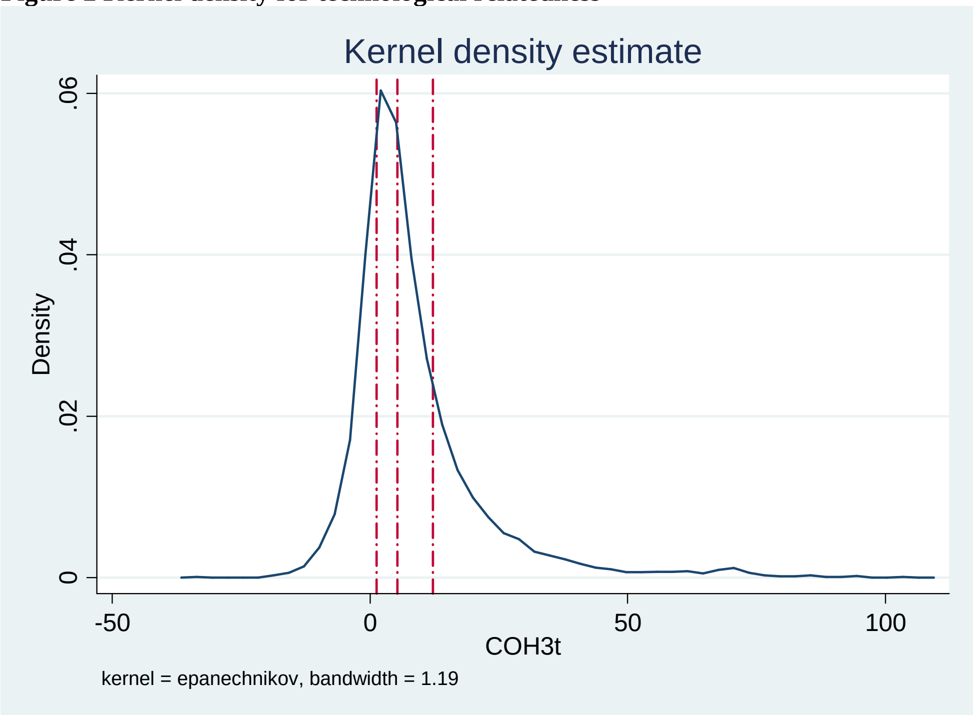
[14] Both measures, the number of fields and the technological relatedness, are derived using the firm's patent portfolio constructed as a three-year moving window of patent applications. Yearly data would generate too much volatility (Nesta and Saviotti 2006) and due to the fact that technology portfolio changes are at least mid-term decisions, three-year moving window of patent applications are used to depict the technological strategy.

Figure 1 Kernel densities for the number of fields



The measure of technological relatedness ranges from -35.46 (less related as expected) to 108.19 (more related then expected). Figure 2 shows the estimated kernel density of the relatedness measure. The distribution is centered around zero with a median value of five. Dotted lines denote the 25, 50 and 75 percent quartiles of the distribution.

Figure 2 Kernel density for technological relatedness



Our results suggest that the majority of firms exhibit a related technology portfolio that might be an indication for a strategic alignment focusing on expansion into related technologies.

V. Econometric specification

Starting with our theoretical model, we move the book value A_{it} to the left hand side and take logs of equation (1). Our fundamental estimation equation becomes:

$$\ln(Q_{it}) = \ln(q_{it}) + \ln\left(1 + \gamma \frac{K_{it}}{A_{it}}\right) + \theta \ln(D_{it}) + \delta \ln(D_{it}) R_{it} + u_{it} \,. \qquad (13)$$

The deviation of Tobin's q from unity thus depends on the ratio of intangible capital to assets, the number of technological fields a company is engaged in research (D_{it}), their relatedness (R_{it}) and a constant denoted by the log of q_{it} which captures its current market valuation coefficient. It should be noted here that by taking the logarithm, we are left with the usual entropy measure in our estimation equations. For explanatory purposes, we will refer to the number equivalent entropy in the upcoming discussion of our results, since the estimated coefficient plus the relatedness adjustment is simply the elasticity of the market value with respect to technology portfolio size.

Two different approaches are present in the literature concerning the treatment of the non-linear term $\ln(1 + \gamma K_{it}/A_{it})$. Approximating the term $\ln(1 + \gamma K_{it}/A_{it})$ by $\gamma K_{it}/A_{it}$ leads to a linear specification of the model[15]. A non-linear estimator has to be applied without this approximation. The accuracy of the approximation depends on the magnitude of K_{it}/A_{it}, generally speaking: the smaller, the better the approximation. Even though a non-linear estimator avoids committing an approximation error, it reveals a major shortcoming because it restricts us to the use of a pooled model without controlling for unobserved heterogeneity. Firms are likely to exhibit various inter-firm differences like unmeasured capital components, monopoly power or market characteristics that influence the magnitude of their individual Tobin's q. Some authors suggest using a pooled non-linear estimator by arguing that the high correlation between individual effects and slowly changing R&D intensities leads to an over-correction of R&D effects[16]. We argue in the opposite direction: high correlation between individual effects, explanatory variables and existing inter-firm differences creates biased coefficient estimates, unless we control for them. The tradeoff occurring when using a linear

[15] Approximation: $\ln(1+x) = x$ if x is small

[16] for instance Hall et al. (2005), Megna and Klock (1993), Czarnitzki et al (2005)

approximation including fixed effects is the risk of a bias due to the approximation of the non-linear logarithmic term.

Approximating $\ln\left(1+\gamma K_{it}/A_{it}\right)$ by K_{it}/A_{it} and defining q_{it} by:

$$q_{it} = \exp\left(d_t + m_i + u_{it}\right), \tag{14}$$

including time effects d_t and observed heterogeneity m_i, leads to:

$$\ln\left(Q_{it}\right) = \gamma \frac{K_{it}}{A_{it}} + \theta \ln\left(D_{it}\right) + \delta \ln\left(D_{it}\right) R_{it} + d_t + m_i + u_{it} \tag{15}$$

Theory provides various approaches to specify the knowledge stock K_{it} of a firm. We follow Hall, Jaffe and Trajtenberg (2001, 2005) who define the knowledge creation process as a continuum from R&D over patents to citations. Every step adds further information concerning the value of innovations. R&D shows the commitment of a firm to promote innovation. Patents are interpreted as an indicator of inventive output and citations measure the extent to which these innovations turn out to be "important" and valuable for the firm (Trajtenberg 1990, Harhoff 1999 et. al.). Instead of dividing all three measures by physical assets – which causes the problem of collinearity in the estimations – ratios according to their position in the knowledge creation process are included. Hence, the basic linear estimation equation is given by:

$$\ln\left(Q_{it}\right) = \left(\alpha \frac{RnD_{it}}{A_{it}} + \beta \frac{Pat_{it}}{RnD_{it}} + \gamma \frac{Cit_{it}}{Pat_{it}}\right) + \theta \ln\left(D_{it}\right) + \delta \ln\left(D_{it}\right) R_{it} + d_t + m_i + u_{it} \tag{16}$$

A first look at the bivariat correlations, as shown in table 2, reveals the expected positive correlations between R&D intensity, citations per patents and the logarithm of Tobin's q. The magnitude of the correlations of Tobin's q differs substantially, from 30 % with citations per patents to 2 % with patents per R&D.

Table 2 Correlation matrix

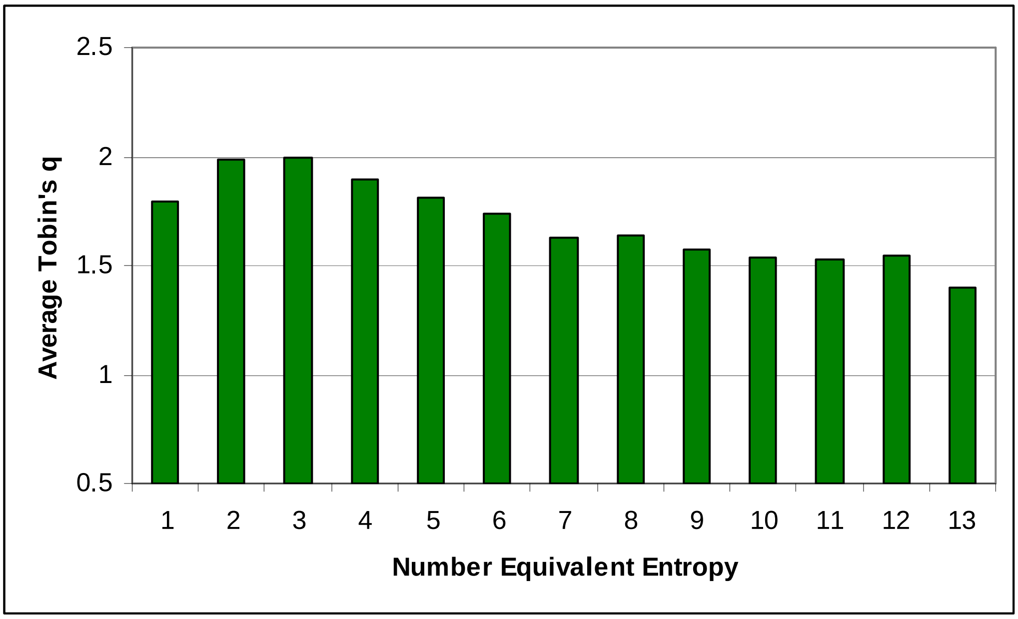
	Log(q)	**R&D/Assets**	**Pat/R&D**	**Cit/Patents**	**Num. equ. Ent.**	**Fields**
log(q)	1.00					
R&D/Assets	0.19	1.00				
Patents/R&D	0.02	-0.05	1.00			
Citations/Patents	0.30	0.17	0.01	1.00		
Number equ. Entropy	-0.14	-0.12	-0.01	-0.15	1.00	
Number of Fields	-0.07	-0.09	-0.01	-0.09	0.85	1.00
Relatedness	0.14	0.07	0.01	0.02	-0.29	-0.17

The number equivalent entropy measure and the number of fields are negatively correlated with the logarithm of Tobin's q, which is in line with the hypothesis of this paper.

VI. Results

A first impression concerning the relationship between the number of technological fields and the market value can be gained by comparing the average q across different numbers of fields. Figure 3 displays the average Tobin's q of firms with approximately the same number of fields in its portfolio. We observe that the average q being maximal for firms covering roughly two or three fields.

Figure 3 Average q and number equivalent entropy[17]



The average q of firms with one field is lower which might indicate that the market appreciates reaching a minimum threshold of diversification. From the second and third field onwards, the average q steadily declines until the seventh field, where q is about 0.4 lower than for a firm working in two fields. Overall, figure 3 shows descriptive evidence for a negative relationship between the number of technological fields and the market value which will be analyzed further in the following.

Table 3 presents empirical results under the linear approximation of the term encompassing the knowledge assets. Starting with the simplest approach to approximate the knowledge stock including patents, citations and R&D, the specification is expanded stepwise by including the number of technological fields, technological relatedness and size corrected measures.

[17] The number equivalent entropy is used here, because we aim to control for the relative importance of each field. Rounded numbers are displayed to obtain a discrete distribution.

Table 3 Estimation results, linear model

	Pooled	Fixed Effects				
log(q)	(1)	(2)	(3)	(4)	(5)	(6)
R&D/Assets	0.094**	0.050*	0.048*	0.046*	0.052	0.046
	(5.114)	(2.320)	(2.218)	(2.166)	(1.746)	(1.497)
Patents/R&D	0.005**	0.004**	0.004**	0.004**	0.004**	0.004**
	(4.038)	(6.738)	(6.978)	(6.974)	(6.335)	(6.353)
Citations/Patents	0.017**	0.007**	0.007**	0.007**	0.007**	0.006**
	(10.150)	(3.583)	(3.525)	(3.480)	(2.850)	(2.764)
Entropy			-0.060**		-0.074**	
			(-3.303)		(-3.044)	
log(Number)				-0.059**		
				(-3.620)		
Entropy * Relatedness					0.002*	
					(-2.326)	
Entropy (corr.)						-0.069**
						(-2.815)
Entropy * Relatedness (corr.)						0.002*
						(-2.406)
log(Sales)						-0.040
						(-1.425)
Constant	0.410**	0.204**	0.292**	0.618**	0.620**	0.807**
	(11.613)	(6.631)	(7.074)	(14.704)	(11.876)	(4.090)
Observations	7826	7826	7826	7826	7084	7084
Number of groups		1007	1007	1007	950	950
R-Squared (overall)	0.163	0.142	0.139	0.123	0.175	0.163

Heteroscedasticity-robust t-statistics in parentheses. All equations include a complete set of year dummies and a dummy for non-reported R&D
* significant at 5 %; **significant at 1%

The estimation results in columns 1 are derived using a pooled OLS model while columns 2 to 6 include fixed effects. The specification in column 1 serves as our benchmark model covering the whole knowledge creation process with R&D, patents and citations. R&D, patents and citations reveal a stable, positive and significant impact on a firm's market value. Column 2 exploits the panel structure of the data by using a fixed effects estimator. A conducted F-test for the significance of individual effects indicates the presence of unobserved heterogeneity. The Hausman-test rejects the hypothesis of zero correlation between individual effects and explanatory variables; therefore fixed effects estimation is used. Still, the impact of R&D, patents and citations remains significantly positive, even though the coefficients became substantially smaller. The largest drop occurs in case of citations per patents where the coefficient reduces to less than half of the pooled one. This might be due to the fact, that a part of the R&D expenditures remains rather stable over time and thereby reducing their explanatory power in the within variation.

Column 3 introduces the entropy measure, which captures the number of technological fields. We find a negative and significant influence with a coefficient of -0.06. This corresponds to an elasticity of the weighted number of technological fields D with respect to the market value of minus 6%. Hence, a firm with equivalent tangible and intangible assets compared to another firm with one equally important field more in its portfolio experiences a market value that is 6% lower. The coefficients of the other variables capturing the knowledge stock are not affected by this expansion of the standard model.

The logarithm of the unweighted number of technological fields is used in column 4 instead of the entropy measure to control for the impact of the weighting scheme in use. We likewise find a negative and significant impact with a coefficient being absolutely similar in size. This is not surprising since the number equivalent entropy is bounded from above by the unweighted count measure. Hence, the number of fields will generally be at least as large as the corresponding weighted measure. The point estimate of -0.06 implies an elasticity of the size of the technology portfolio with respect to Tobin's q of 6% without controlling for the relatedness of the portfolio and thereby neglecting to distinguish between the different effects of economies of scale and scope.

Column 5 turns to the estimation of the full model and takes a closer look at the composition of the technology portfolio by introducing the measure of technological relatedness. Since only companies with large portfolios can exhibit technological relatedness, the analysis is restricted to firms being engaged in at least two technological fields. The parameters encompassing the knowledge creation process remain stable compared to the fixed effects regressions of table 3. All of them exhibit a positive influence on Tobin's q and are mainly significant at the five percent level. As expected, the coefficient of the interaction term points in the opposite direction, suggesting a counterbalancing effect in case of large and related technology portfolios. The elasticity of the size of the technology portfolio with respect to Tobin's q rises when the relatedness of the portfolio increases. Evaluated at median relatedness and entropy, we find a discount of 6% per additional equally important field. This discount reduces to 4% for the 75% quartile of the distribution of relatedness, implying that highly related technology portfolios experience a smaller loss We believe this relationship is due to the fact that the ability of firms to exploit economies of scope reduces when enlarging its technology portfolio to unrelated fields, while spreading into related areas increases the possibility to benefit from economies of scope, which may reduce costs and thereby increase future profits.

Furthermore, we construct a size-corrected entropy measure in column 6 by regressing the entropy and the interaction term on the logarithm of sales and utilizing the residuals since some authors argue that portfolio size is mainly driven by firm size. This leaves us with the opportunity to include sales as a further explanatory variable. Both coefficients are hardly affected by this correction, which can be taken as further evidence for the robustness of our results and as the absence of a size effect in our analysis.

Now, we compare the estimation results for the linear approximation with the exact non-linear specification of the model; table 3 displays the corresponding estimation results. In contrast to the linear specification in equation 14, the parameters of R&D, patents and citations in the non-linear pooled model of table 4 exceed those of pooled OLS and fixed effects in table 3. The difference in size between pooled OLS and pooled non-linear is caused by the linear approximation of the logarithm. However, one could also argue that the pooled model overestimates the coefficients by ignoring individual firm specific effects and their correlation with the explanatory variables.

As expected, the coefficients of the entropy measure and the interaction term are comparable in signs to what is found in the linear model, presumably because they are mainly unaffected by the linear approximation. However, the coefficient of the interaction term became substantially larger which enhances the role of relatedness. In contrast, the coefficient of the number of fields – the entropy measure – got smaller. Overall, this will lead to a reduction in the corresponding elasticity. This change might be caused by estimating the non-linear term directly, since the explanatory power of the variables representing the knowledge creation process increases. Again, we calculate the elasticity of the size of the technology portfolio with respect to Tobin's q for various degrees of relatedness. Evaluated at mean entropy, we observe a discount of 4% per additional field at the 25% quartile of the distribution. At the median, this reduces to 0.6%, so approximately zero. For high levels of relatedness, we find a positive elasticity, e.g. 5% for the 75% quartile. Hence, the firm benefits from additional equally important fields by exploiting economies of scope through a common knowledge base.

Table 4 Estimation results, non linear model

	Non Linear		
log(q)	(1)	(2)	(3)
R&D/Assets	0.291**	0.306**	0.166**
	(8.462)	(8.512)	(8.308)
Patents/R&D	0.018**	0.023**	0.013**
	(4.905)	(6.074)	(5.425)
Citations/Patents	0.045**	0.047**	0.034**
	(11.196)	(10.713)	(10.981)
Entropy	-0.051*		-0.043
	(-2.277)		(-1.937)
Entropy * Relatedness	0.006**		0.007**
	-5015		-6177
Entropy * Relatedness (p25)		-0.056*	
		(-2.422)	
Entropy * Relatedness (p50)		-0.054*	
		(-2.280)	
Entropy * Relatedness (p75)		-0.041	
		(-1.466)	
Entropy * Relatedness (p100)		0.022	
		(0.631)	
High-Tech Industry			0.100
			(-1.882)
Stable Tech Industry (long)			-0.115*
			(-2.005)
Stable Tech Industry (short)			-0.002
			(-0.027)
Observations	7084	7084	7084
R-squared	0.438	0.429	0.450

Heteroscedasticity-robust t-statistics in parentheses. All equations include a complete set of year dummies and a dummy for non-reported R&D
* significant at 5 %; **significant at 1%

In order to analyze the impact of portfolio size adjusting for relatedness, dummy variables are generated for the quartiles of the relatedness measure and interacted with the entropy measure. Firms belonging to the lowest level of relatedness, the 25% percentile, exhibit a significantly negative impact of -0.056. This corresponds to an average discount for firms with unrelated portfolios of nearly 6% per additional field. The coefficient for the second quartile is again negative and significant and comparable in size. In case of on average related portfolios – the upper 50% of the distribution – the results are less compelling. Even though we observe larger coefficients which are in line with our story, they are not significant. Column 2 indicates that the negative impact on the market value diminishes as the relatedness within the portfolio rises since a significant discount occurs only in case of unrelated portfolios.

In column 3, we include industry effects according to segments developed by Chandler (1994) that are based on technological dynamics. Even though the distinction between high-tech, stable-tech and low-tech industries seems to be quite rough, it shows that the coefficient of our measure of technological diversification is not driven by some sort of technological fixed effect that affects only a couple of industries. As expected, firms in high-tech industries experience a significantly higher Tobin's q on average. In contrast, there is no systematic difference in the market value of stable-tech industries.

VII. Conclusion

The aim of this paper was to analyze the impact of a firm's technology portfolio on its market value. Two concepts were used to describe a firm's portfolio: the number of fields and the relatedness of the technologies covered by a firm in research. Based on a theoretical framework using an expanded Tobin's q approach, it presents evidence for a negative influence of portfolio size on the market value caused by a diminishing potential to make use of economies of scale. This discount can be counterbalanced when the relevant fields share a common technological base which is measured by the degree of technological relatedness.

In the linear version of our model, we find an elasticity of the size of the technology portfolio with respect to Tobin's q, evaluated at median relatedness and entropy, of 6% per additional equally important field. This discount reduces to 4% for the 75% quartile of the distribution of relatedness, implying that highly related technology portfolios experience a smaller loss. The picture slightly changes when applying a nonlinear estimator: evaluated at mean entropy, we observe a discount of 4% per additional field at the 25% quartile of the distribution. At the median, this reduces to 0.6%, so approximately zero. For high levels of relatedness, we find a positive elasticity, e.g. 5% for the 75% quartile. Hence, the firm benefits from additional equally important fields by exploiting economies of scope through a common knowledge base.

Generally speaking, enlarging the technology portfolio in unrelated fields negatively influences the market value of a firm due to the fact that it reduces the ability to exploit future economies of scale and scope. In contrast, spreading into related areas increases the possibility to benefit from economies of scope, which reduces future costs and thereby increases future profits.

Our results suggest that under the objective of value maximization, the composition of the research portfolio plays an important role for valuation by financial markets. The possibilities to exploit economies of scale and scope should be considered when deciding to expand research activities into new areas and the relatedness of the current research portfolio and the intended new field or fields should be taken into account. A properly designed – meaning related – research portfolio can have substantial influence on future profits and thereby on the market value.

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Appendix 1

Classes within the U.S. Classification System
December 2006

1) Superconductor Technology: Apparatus, Material, Process
2) Nanotechnology
3) Life and agricultural sciences and testing methods
4) Stock materials; articles (e.g., layered products, filters, batteries)
5) Compositions and synthetic resins; chemical compounds
6) Chemical processing technologies: processes and apparatus (e.g., wave energy, metallurgy, separatory contacting)
7) Calculators, computers, or data processing systems
8) Information storage
9) Measuring, testing, precision instruments
10) Electricity, heating
11) Electro-mechanical systems
12) Electricity: subsystems, components, or elements
13) Ammunition, weapons
14) Body treatment care, adornment
15) Apparel and related arts
16) Plant and animal husbandry
17) Teaching
18) Amusement devices
19) Foods and beverages: apparatus
20) Heating, cooling
21) Buildings
22) Receptacles
23) Supports
24) Closures, partitions, panel
25) Textiles
26) Earth working and agricultural machinery
27) Check-Actuated control mechanisms
28) Dispensing
29) Material or article handling
30) Fluid handling
31) Vehicles
32) Motors, engines, pumps
33) Coating, printing, and printed material; stationery, books
34) Manufacturing, assembling, including some correlative miscellaneous products
35) Cutting, comminuting, and machining
36) Miscellaneous treating
37) Handling or storing sheets, webs, strands, and cable
38) Machine elements or mechanism
39) Miscellaneous hardware
40) Tools
41) Joints and connections
42) Fastenings

Appendix 2[18]

Chandler Segment[19]	SIC Description	SIC Code
High-Tech: 1	Electronic computing equipment	3570-3573 3575 3576 3577
	Calculating machines excl. comp.	3578
	Refrigerating & heating equip. (comml)	3580-3582 3585 3589 3596
	Power distribution & transformers	3612
	Switchgear & switchboard apparatus	3613
	Motors, generators & industrial controls	3600 3620 3621 3622 3625
	Electronic & electric coils & connectors	3524 3677
	Household refrigerators & freezers	3630 3631 3632 3633 3635 3639
	Lighting fixtures & equipment	3640 3641 36425 3646 3647 3648
	Primary & storage batteries	3691 3692 3693
	Engine elctrical equipment & misc	3694 3699
	Electronic & electric connections	3643 3644 3678
	Electronic signaling & alarm systems	3669
	Radio & TV broadcasting sets	3663
	Radio & TV receiving sets	3651
	Records, magnetic, &optical recording	3652 3690 3695
	Communication equipment	3661 3662 3669 4810 4812 4813
	Electron tubes	3671
	Semiconductors & printed circuit boards	3672 3674 3675 3676
	Electronic components, computer acc.	3670 3679
	Engineering scientific instruments	381x
	Measuring & controlling devices	382x
	Aircraft parts & engines	3720 3721 3724 3728
	Ship & boat building & repairing	373x 3795
	Railroad equipment	374x
	Complete guided missiles, aerospace	376x
	Optical instruments & lenses	3827
	Dental equipment & supplies	3843
	Surg. & med. inst., appliances, & supplies	3840 3841 3842
	X-ray apparatus	3844
	Photographic equipment & supplies	3861
	Electromedical apparatus	3845
	Pharmaceuticals	283x
	Opthalmic goods	3851
Stable-Tech: 2 (long horizon)	Industrial inorganic chemicals	281x
	Plastic materials & resins	282x
	Paints & allied products	285x
	Industrial organic chemicals	286x
	Fertilizer	287x
	Explosives & misc. chemicals	289x
	Asphalt, roofing & misc coal/oil prods	2950 2951 2952 2990 2992 2999
	Petroleum & refining	291x 1311 1389
	Steelworks, rolling & finishing mills	331x
	Iron & steel foundries	332x
	Primary metal products	339x

[18] Source: Hall and Vopel (1997)
[19] Segments (High-, Low- and Stable-Tech) were derived by Chandler (1994) and modified by Hall (1994).

	Prim aluminum smltg, reg, roll, &draw	3334 3353 3354 3355
	Primary smeltg & refing (non-ferrous)	3330 3331 3332 3333 3339
	Secondary smeltg & refing (non-fer.)	334x
	Rolling, drawing, & extruding of nonferr.	3350 3351 3356
	Drawing & insulating of nonfer. wires	3357
	Nonferrous metal casting	336x
	Turbines, generators, & combustion eng.	351x
	Lawn, garden & farm mach. & equip.	3523 3524
	Const. & mining mach. & equip.	3530 3531 3532
	Oilfield machinery	3533 3534
	Conveyors, ind. trucks&cranes, monorails	3535 3536 3537
	Mach. tools, metalworking eq. & acc.	354x excl. 3548
	Special industrial machinery	3550 3559
	Food prods & packaging machinery	3556 3565
	Textile machinery	3552
	Wood & paper industry machinery	3553 3554
	Printing trades machinery & equip.	3555
	Pumps & pumping equip.	3561 3586 3594
	Ball & roller bearings	3562
	Compressors, exhaust., & ventilation fans	3563 3564 3634
	General industrial machinery	3560 3568 3569 359x
	Ind. high drives, changers & gears	3566
	Industrial process furnace ovens	3567 3558
	Scales & balances excl. laboratory	3596
	General office machines	3579
	Motor vehicles	3711 3713 3715 3799
	Motor homes	3716 3792
	Motorcycles & bicycles	3751 3790
Stable-Tech: 3 (short horizon)	Tires & innertubes	301x
	Plastic products	307x 3080 3084-3089
	Unsupported plastics, films &sheets	3081 3082 3083
	Packing & sealing dev. & fab. rubber nec	3050 3051 3052 3053 3060 3061 3069
	Glass & glass products	321x 322x 323x
	Cement	324x
	Structural clay products	325x
	Pottery & related products	326x
	Concrete, gypsum & related prods	327x
	Abrasive asbestos & mineral wool prods	329x
	Metal cans & containers	3411 3412
	Cutlery & hand tools	342x
	Heating equipment & plumbing fix.	3430 3431 3432 3433 3437 3467
	Fabricated structural metal	344x
	Screw machine products, bolts, nuts	345x
	Metal forgings, plating & coating	346x 347x
	Wire springs & misc. metal prods.	3495-3499
	Ordnance & accessories	348x
	Valves & pipe fittings	3490 3491 3492 3493 3494
	Perfumes & toilet prods.	2844
	Soaps & cleaning products	2840-2843
	Motor vehicle parts & accessories	3714
Low-Tech: 4	Meat products	2010 2011 2013 2015 2016
	Dairy products	2020 2021 2022 2023 2024 2026

Canned & frozen foods	2030-2032 3037 2038 2053 3091 3092
Processed fruits & vegetables	2033 2034 2035 2068 2096
Breakfast cereals	2043
Animal feed	2047 2048
Grain mill products	2040 2041 2044 2045
Wet corn milling	2046
Bakery products	2050 2051 2052
Sugar chocolate & cocoa prods.	2060-2067
Fats & oils	207x
Malt & malt beverages, alcoholic bev.	2082 2083 2084 2085
Soft drinks & flavourings	2080 2086 2087
Miscellaneous preproduced food	2090 2095 2098 2099
Tobacco products	21xx
Textile mill products	22xx excl. 2270 2273
Rugs	2270 2273
Apparel	23xx 3965
Footwear, rubber & leather	3021 314x
Leather & leather products	310x-313x 315x 316x 317x 319x 3961
Logging & sawmills	241x 242x
Millwork, veneer & plywood	243x 2450 2451 2452
Wood products	244x 249x
Household furniture	251x
Office furniture	252x
Shelving, lockers, office & store fixtures	253x 254x 259x
Pulp, paper & paperboard mills	261x 262x 263x
Industrial paper & paper products	2600 264x 265x 266x
Converted paper - household use	267x
Commercial printing	275x 2796
Printing & publishing	27xx excl. 275x 2796
Musical instruments	3931
Sporting & athletic goods	3949
Dolls, games & toys	3942 3944
Pens, pencils, & other office & artists mat.	395x
Misc. manufacturing industries	399x
Jewelry & watches	3873 3910 3911 3914 3915 396x