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Diversity and quality in technology portfolios

The impact of technological diversification on technological capabilities of firms: Empirical evidence from Germany

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Abstract (210 words)

Technological diversification at the firm level has been identified as a persistent and industry-overarching phenomenon and its firm-endogenous and exogenous determinants and, more recently, its effects have widely been addressed in the literature. This empirical paper investigates the relationship between technological diversification and the development of technological capabilities of firms. Hence, it provides a contribution to the literature on performance effects of technological diversification. Whereas prior research in the field predominantly conceptualizes and measures technological capabilities via the quantitative technological output of a firm, e.g. via the number of patent applications or grants, the qualitative component of technological capability and performance has been widely neglected so far. We try to fill this gap by expanding the scope of analysis: Various empirical indicators are used to assess the technological capabilities by means of technological quality and coherence in a firm's technology portfolio. The conceptual model that is developed alleges a non-linear relationship between technological diversity and technological capabilities, which is moderated by the level of coherence of the technology portfolio. Adopting a truncated regression model, the existence of an inverted U-shaped relationship of technological diversification and technological quality is tested empirically on a data set of German industrial engineering and automotive firms (consolidated conglomerates) over a period of 25 years (1984-2008).

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Introduction

Empirical studies show that, as products and processes are becoming ever more multi-technological in nature, both medium-sized and large multinational corporations tend to continuously increase the diversity of their technological competencies, irrespectively and in spite of vertical specialization (Torrisi & Granstrand 2004; Stephan 2010). Moreover, the generated variety among technologies is usually larger than the unfolding product variety (Patel & Pavitt 1997; Granstrand 1998). Multi-technological firms combine new technologies with existing (technical) capacities and resources, generating new technological opportunities that change and impact on established corporate and industry paradigms and to some extent massively challenge incumbents in 'old' technology fields. Eventually, the phenomenon can be described as an evolutionary process in which entries (and exits) into technological fields occur along path-dependent technological trajectories (Dosi 1982; Cantwell 2004).

While the research within this field in its beginnings predominately focused on determinants of the phenomenon, more recent studies increasingly address and empirically investigate success factors and performance effects of technological diversification. This raises the issue of finding adequate and valid performance measures.

Theoretical background and hypotheses

Determinants of technological diversification at the firm level

The appropriation of the terminology *technological diversification* can be ascribed to Kodama (1986). Herein, technological diversification (at the industry level) is defined as "*each sector's R&D activity outside its principal product fields*" (Kodama 1986). The expansion of technological activities, at this level of analysis, is found to be determined by industry specific factors and, especially, the exploration of new technological opportunities (Pavitt et al. 1989). Central unit of analysis within this framework is the technology base of a firm, represented by the total of technological resources and competences that a firm acquires and controls due to its research activities and the development of its products and services (Granstrand & Sjölander 1990). Technological diversification leads to a reduction of concentration in a firm's ancestral technology fields and to more uniform distribution of the technological resource profile over a variety of technology fields (Pavitt et al. 1989). From a cost-based perspective the buildup and the expansion of technological resources is connected to initial investments with fix cost character and comparatively low variable costs for subsequent utilization and replication due to the intangibility and infinite transferability of technological knowledge.

Some general characteristics and patterns concerning the manifestation of this phenomenon have been identified: Technological diversification generally precedes a firm's product or business segment diversification, since the exploitation of a wide spectrum of technological resources most often constitutes a necessary precondition for an expansion of the range of product and services (Pavitt 1998; Penrose 1959). Moreover, it is mutually determined by technology-based diversification at the output level, which originates from the availability of *generic* or *platform technologies* (Granstrand 1999; Argyres 1996.; Teece 1997.; Penrose 1959). Those lead to increased capital yield and are generated from network externalities and processes of knowledge accumulation. Furthermore, they determine technological path-dependencies and the creation of technological trajectories at the firm level (Kim & Kogut 1996). Accordingly, the pattern of technological diversification of single firms remains relatively constant and stable over time. It only changes gradually due to the inertia of specialization of incremental knowledge and competence development (Cantwell & Andersen 1996; Patel & Pavitt 1997; Dosi 1982).

There are several drivers for the rise of technological diversification among firms. One crucial factor is increasing complexity, seen in products and processes, requiring firms to invest in a growing variety of technologies over time (Granstrand & Sjölander 1990). This is only apparently at odds with technology outsourcing, since the latter makes it indispensable for firms to keep up a high and eclectic absorptive capacity for the efficient assimilation of externally acquired technologies (Cohen & Levinthal 1990.; Granstrand et al. 1997). Likewise, rising systematic interdependencies along the value chain require firms to build up competences in technological domains of suppliers and buyers in order to ensure persistent system integration capabilities (Pavitt et al. 1989; Stephan 2003; Stephan 2010). A further driver of technological diversification consists in the exploration and experimentation of firms with new technologies by means of *trial-and-error processes*, which become manifest especially in the aftermath of the occurrence of radical and disruptive innovations (Patel & Pavitt 1997; Granstrand & Sjölander 1990).

Finally, the event of technological diversification at the firm level can be substantiated by the accrual of technological and competence-based *excess resources* as the result of learning effects in R&D, which lead to higher efficiency in resource utilization over time. Whereas R&D resources exhibit high factor specificity, their disposal is related to increased transaction costs and, thus, firms often prefer internalizing newly accessed technology fields over a market solution (Penrose 1959; Teece 1980; Williamson 1990).

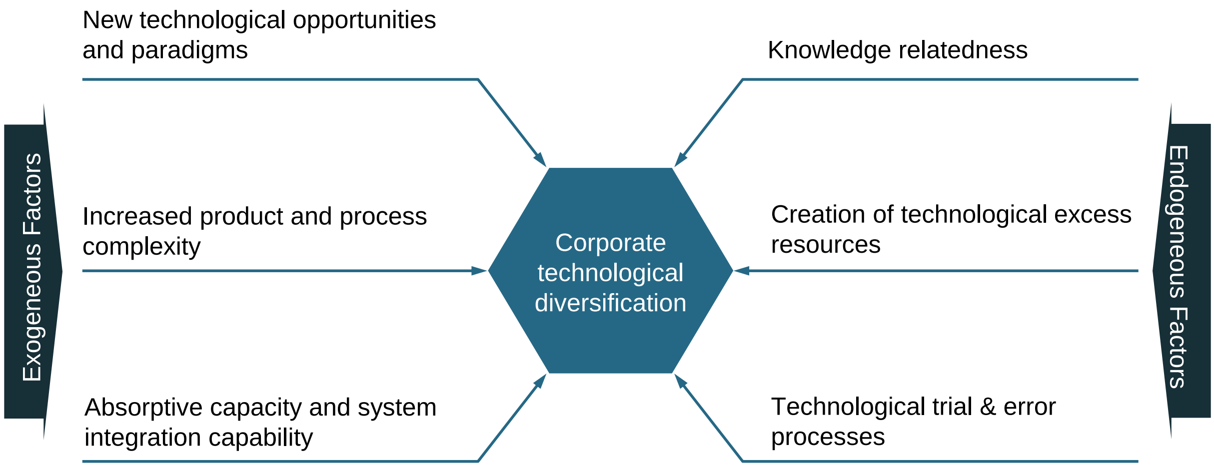
The previous characterization depicts the importance of cumulativeness and path-dependencies as fundamental components of the determinants of technological diversification. In fact, firms most often pursue coherent patterns of technological diversification (Teece et al. 1994). Here, *coherence*, in a broader sense, refers to a non-random distribution of technological activities over technology fields, which is primarily determined by the existence of *knowledge-relatedness* between technologies, i.e. which rely on common or complementary knowledge bases or build upon common scientific principles or heuristics (Breschi et al. 2003; 2004). The defining dimensions of knowledge-relatedness are: 1. *proximity*, which is normally the result of learning spillovers (unintended technological diversification) and local learning effects (intended technological diversification) (Henderson & Cockburn 1996; Malerba 1992; Nelson & Winter 1992; Dosi 1982.). 2) *commonality*; i.e. one and the same type of knowledge can be deployed as a *common resource* for several technologies and, hence, synergies can be realized (Teece 1982; Penrose 1959), and, finally, 3. *complementarity*[3], where relatedness does not originate from similarities between technologies, but rather from their required joint application (Pavitt 1998). This refers also to the creation of generic technologies, i.e. highly pervasive complementary technologies that are suitable to be used in combination with a large variety and a broad range of technologies (Arora & Gambardella 1994; Bresnahan & Trajtenberg 1995). It has been observed that technological complementa-

[3] Knowledge complementarity in the literature is sometimes also referred to as *technical complementarity* (e.g. Breschi et al. 2004). In fact, this terminology appears to be more accurately and adequately chosen, since the concept of complementarity herein refers directly to the technical applications of of a firm's knowledge-base rather than to the knowledge-base itself.

rity, indeed, exerts the largest significant influence on the increase of technological diversification (Fai 2003).

By contrast, a pattern of seemingly unrelated technological diversification refers to an expansion of a firm's technology base into fields where hereditary competencies and accumulated knowledge cannot be applied. Hence, it represents an explorative strategy of diversification by means of which new competencies are added to existing ones, creating highly innovative potentials (Quintana-Garcia & Benavides-Velasco 2008). This is accompanied by higher resource expenditure, since firms need to span bigger gaps between ancestral and new technologies. Moreover, cumulative propensities and path dependencies raise significant entry barriers to new technology fields.

Figure 1. Determinants of technological diversification at the firm level



Divergence in the type and degree of technological diversification among firms

Differences in technological diversification among firms are in the first place determined by exogenous influence factors at the industry level and by the macro-technological environment a firm operates in. As observed by Stephan (2003), there is a positive linear relationship between both the dynamic of technological change and the complexity of products –determined by industry affiliation – and the level of technological diversification. Moreover, the pattern of technological diversification of an industry changes over time, affecting the participating firms, whereas again there are industry-specific differences (Fai 2003).[4]

Differences among firms' technological diversification profiles at the intra-industry level, on the other hand, can be explained, generally, by heterogeneity and idiosyncrasy of resources and, more specifically, by explanatory approaches from evolutionary economics. Technological trajectories, as described by Dosi (1982), are characterized by path dependencies and specificity, resulting from the distinct cumulative nature of learning processes. From an evolutionary economics perspective, technological trajectories and paradigms to be understood as the result of continuous variation, selection and retention processes, which oftentimes lead firms to considerably migrate from their original core technology area over the course of their history (Nelson & Winter 1982; Cantwell 2004). Technological diversification can, hence, contribute to the avoidance of negative lock-in effects and actively promote the development and business model innovation of a firm (Suzuki & Kodama 2004). Then again, intra-industry variance of technological diversification can be explained by non-rational approaches, drawing from management and behavioral theory, according to which the evolution of the technological resource base of a firm mirrors past management decisions in the face of technological complexity and uncertainty (Argyres 1996; Patel & Pavitt 1997).

Finally, structural aspects have their impact on the development of firm-specific competence and technology bases. Fewer divisional boundaries within a corporate structure generally lead to a larger expansion of the technological resource base, while stronger divisional demarcation leads to focused improvement of core competencies (Argyres 1996). A centralized group's R&D division has been found to have a tendentially stronger positive impact on the level of technological diversification compared to a decentralized R&D organization (Argyres & Silvermann 2004).

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[4] For instance, is has been observed that the electrical and the mechanical engineering industries as well as the automotive industry have exhibited rather cyclical developments, whereas the chemical industry has witnessed a continuous increase in technological diversification on the past century (Fai 2003).

Success factors and risks of technological diversification

Several empirical studies have focused on evaluating the (diversification) performance of an expansion of technological resources, both from a classic strategy research perspective, based on its input to generating added firm value, and, from a perspective of technology and innovation research, based on its influence on the innovation performance of firms (e.g. Chen et al. 2013; Miller 2006; Griliches 1981).

The performance effects of technological diversification are predominantly determined by firm-endogenous factors.[5] In view of shortening (product) lifecycles and a growing myriad of technological options, the internal capability of effectively integrating existing with new technologies in this context plays an even more important role than the sheer ability of creating new technologies (Subramaniam & Youndt 2005). In this regard in particular, technological diversity can be seen as a *response pool* of purportedly slack resources conferring resilience in the face of incertitude and, thus, allowing to hedge against ignorance, i.e. situations with no grounds for probabilities and no basis for definition of a comprehensive set of outcomes (Stirling 1998). The disposability of such a response pool enables firms to become technologically versatile and, hence, more flexible and resilient against (technological) disruption.

Likewise, the benefits of a diversified knowledge base are underpinned by organizational learning theory. Accordingly, expanding a firm's technology base to find new or complementary solutions to technical problems may induce an acceleration of the rate of invention. As the repeated application of a specific bundle of technologies may in the long run lead to exhaustion of technically possible combinations, it is auspicious advice for firms to dispose of a broad stock of technologies, whose concrete applicability may become apparent only at a later point in time or under changed requirements and conditions (Kim & Kogut 1996; Levinthal & March 1993). This, in addition, exerts a positive effect on the accumulation of absorptive capacity (Cohen & Levinthal 1990). In absence of these capabilities, firms will not be able to recognize the importance of new technological opportunities in early stages of the technology life cycle in their extended technological environments and, furthermore, lack the ability to

[5] The influence of external, industry-specific factors is mostly limited to 'me-too' companies, i.e. those firms that are neither industry leaders nor losers (Hawawini et al. 2003).

successfully exploit the latter, which may put at risk a dynamic competitive advantage. Hence, technological diversification bears a preventive effect against the threat of core rigidities (Leonard-Barton 1992; Suzuki & Kodama 2004, Stirling 1998). Companies with a broad technological resource base have in general more strategic options concerning external acquisitions, licensing, forging strategic alliances or the internal development of technologies to build up research competencies and yield innovations (Kogut & Zander 1992).

Against this backdrop, Granstrand (1999) outlines five substantial revenue-related potentials for success from technological diversification: 1) *static economies of scale*, which relate to the opportunity a technology-based diversification due to the existence of generic technologies; 2) *dynamic economies of scale*, which accrue due to the non-scarcity of knowledge as well as its augmentation through learning processes; 3) *economies of scope through cross-fertilization* between existing and new technologies, enabling the creation a new inventions, functionalities and enhanced product and process features; 4) *economies of speed*, determined by the fact that intra-firm technology transfer takes place more swiftly and is associated with less transaction costs compared to inter-firm boundaries transfer; and 5) *economies of space*, which originate from the increased absorptive capacity of technologically diversified firms with regards to spatially determined technological spillover effects.

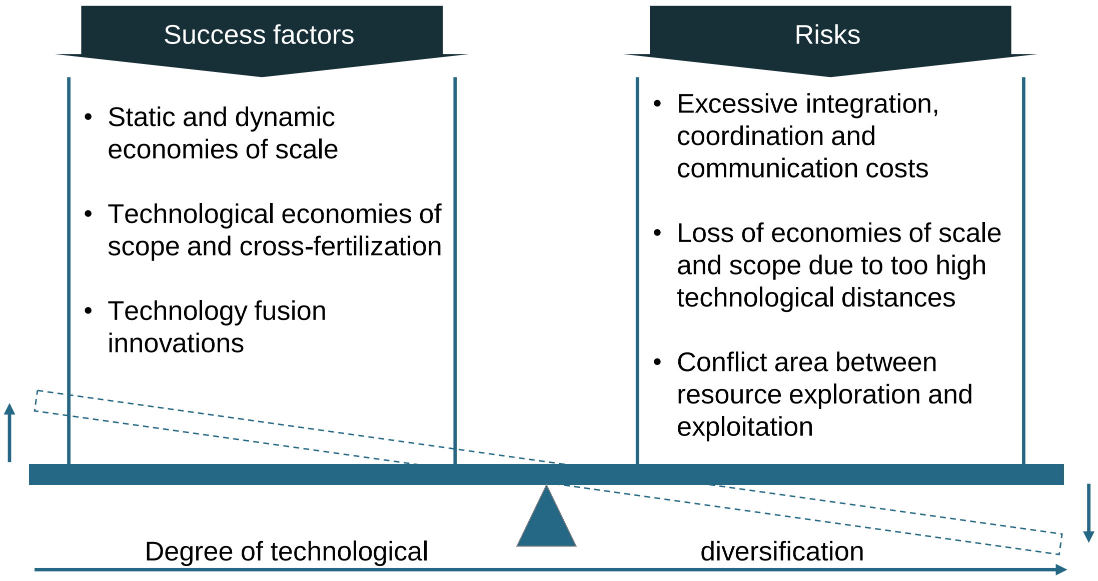
Regarding the involved resource application and classification of the search mode, the dichotomous differentiation between related (strongly coherent) and unrelated (weakly coherent) types of technological diversification can easily be transferred to the distinction between organizational resource exploitation and exploration, as established by March (1991). Incidentally, it needs to be specified that, on the level of the resource base of a firm, technological diversification exerts a more explorative than exploitative influence (Quintana-Garcia & Benavides-Velasco 2008). The weighting of exploration rises with the increase of the level of technological diversification.

Thus, it becomes evident that technological diversification can be associated also with increased costs and potential risks. In particular, it bears the hazard of firms being tempted to diversify ‘too broadly’ and, accordingly, lose the ability to cultivate the required profound competencies in a specific technological core domain, which are necessary to realize economies of scale in technology development. Moreover, a higher degree of technological diversification leads to increased integration, communication and coordination costs for firms, which particularly arise when firms attempt to combine rather mature, existing, with nascent technologies that are not compatible with the dominant core technologies or conflict with the latter in some kind of way (Granstrand 1998). In this manner, an expansion of the technology base can lead into a trap of ‘over-diversification’, causing negative synergies and diseconomies of scope with escalating costs that outweigh the economic and technological potential (Lin et al. 2006).

By extending this to the Schumpeterian notion of creative destruction, a conflict area between the expansion of technological competencies into new fields and the simultaneous deepening of existing core competencies is revealed (Granstrand 1997). Incumbent firms are particularly exposed to these conflicting forces, since they are challenged to advance the parallel exploitation of often multiple and yet individually rigid core-technology and -competence areas. It appears unfeasible for firms to be efficiently productive and flexible in technology development at the same time (Benner & Tushmann 2003; Leonard-Barton 1992). Very recently, though, Kim et al. (2016) find that, albeit both insufficient and excessive technological diversification are detrimental to firm growth, the harmful effect of over-diversification on growth is mitigated for those firms who present high levels of competence in their core technology fields. Hence, it is indispensable for the optimal realization of the potentials of a strategy of technological diversification to keep the ambidextrous balance between exploitation of core-technology competencies and exploration of new domains of knowledge, in order to sustain and expand a strong competitive position through combined processes of knowledge generation, adaptation and consolidation.

In the light of the foregoing, the existence of a complex, non-linear relationship between the degree of technological diversification and the technological performance of firms becomes evident. The assumption of an inversely U-shaped progression of the underlying relationship has already been to some extent empirically supported in the literature (Leten et al. 2007; Huang & Chen 2010).

Figure 2. Potentials and associated risks of technological diversification



Technological quality and capabilities

At this point the evaluation of performance effects of technological diversification shall be extended to the dimensions of quality of innovative activity and, accordingly, the technological capabilities of firms. Those appear as extremely latent constructs, depending on a multiplicity of firm-external and -internal influence factors, which can usually not be captured or measured in a direct way, because of their strong subjective character and high context specificity. In fact, as for other types of firm-specific resources as sources of competitive advantage, technological resources that ought to be valuable, rare, inimitable and not substitutable in the (conceptually founded) logic of the RBV, also appear to be difficult to assess, manipulate, or deploy and, hence, difficult to exploit, making them hardly amenable for empirical testing (Priem & Butler 2001). Nevertheless, it is indeed possible to draw on proxy measures in order to infer the technological value or quality of inventions, allowing for the formulation of falsifiable propositions within this confined scope of analysis. In particular, patent based data has become an established and validated indicator in this regard over the years. In fact, patents are not only passive codifications of technological inventions, but provide a multitude of detailed and valuable information about intra-organizational processes and behavior of strategic actors within complex institutional frameworks (Gittelmann 2008). Given consistently expanding patent databases and portfolios and the already dramatically left skewed distribution of patent values over the number of patent applications, ensuring validity and reliability in the analysis of raw patent data from a merely quantitative level becomes more and more difficult (van Zeebroeck 2011). Here, the measurement of the construct can be achieved, on the one hand, by means of indicators that directly or indirectly correlate with observable prices, costs or sales volumes of patent protected products or, on the other hand, by through indicators that operationalize latent determinants of patent quality, e.g. the degree of novelty, the comprised inventive step, the breadth, the strength of conveyed protection, disclosure or the dependency of complementary resources of single patents (Reitzig 2004).

At this point it should be adverted that the quality or technological value of a technology for a firm cannot necessarily be equaled to patent value. This derives from the fact that patenting is not the only feasible way of commercially exploiting and appropriating rents from a technology. Likewise, technologies are often protected by a bundle of patents which determines inevitably that the value of a single patent of the bundle will be inferior to the actual value of the underlying technology. In addition, patent quality is also significantly sensitive for size effects (Bessen 2008). The technological quality of an invention does in the first instance not allow for inference to the economic relevance of the technology, i.e. the monetary success and the competitive impact of a patent (Fischer & Leidinger 2014). Nevertheless, despite the multi-factorial complexity of the underlying relationship, several empirical studies provide support for existing links between these two performance levels; Hall et al. (2005) have observed a positive relationship between the average patent quality and the market valuation of a firm, while it has been found that, at least in some specific industries (e.g. pharmaceuticals), a patent's quality and scope are significantly related to the introduction of new products and, to some extent, to profitability (Markman et al. 2004).[6] Hence, under some constraints, individual technologies or inventions can indeed be considered as individual, specific resources that are directly related to superior firm performance. Moreover, patents that combine a broad range of distinct sources, types and approaches of knowledge are particularly versatile in their

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[6] Precisely, Hall et al.'s (2005) findings indicate that if a firm's patent quality increases so that on average the patents in the stock receive one additional citation, the firm's market value would increase by 3%. Markman et al. (2004) start from the assumption that patents, as per definition, are valuable and rare and focus on the RBV's defining constructs of inimitability and non-substitutability of resources, operationalized through citations and patent claims. Moreover, they limit their analysis to a subset of firms from the pharmaceutical industry. Albeit providing a valuable contribution towards the attempt of validating the RBV as a theory, these factors obviously restrict the unconditional generalizability of their findings.

application, which again has a positive impact on valuation of technological quality (Trajtenberg et al. 1997). For the research interest of this paper patent quality, as a proxy for capability, provides an excellent and sophisticated measure.

Hypotheses

Synergies and economies of scope are to a great extent originated through knowledge-relatedness within the technology base. Hence, by coherently diversifying into technology fields with a high level of relatedness to its core technological domains, a firm can realize these effects and thereby increase the complexity of its knowledge base and, accordingly, exploitatively improve the quality of its technologies and, ultimately, products. Moreover, by pursuing a delimited explorative technological diversification into more distant technology areas, new competence fields can be developed and technological opportunities can be embraced. This enables a firm in a non-probabilistic setting to hedge against ignorance for unanticipated exogenous developments within the environment of the firm. The thereby ongoing evolutionary processes of variation and selection are also likely to exert a quality-enhancing influence on the technological trajectories of a firm. Hence, it can be assumed that technological diversification, at first instance, has a strong positive impact especially on originality, as a measure that directly relates to the applicability and usefulness of coherence within the technology base. Then, on the other hand, technological diversification bears the danger of inefficient knowledge accumulation through over-diversification, within which the accessed areas of knowledge are increasingly too distant from each other to ensure even complementary knowledge-relatedness. Furthermore, technology quality, as well as the quantitative innovation output, is highly dependent of the efficient allocation of organizational resources. When the available resources in R&D are dispersed over a too large amount of distinct research fields, the necessary local capacities may be lacking to develop deeper core competencies in at least one technology area, with a then detrimental impact on technology quality. These considerations, hence, lead to the formulation of the following hypothesis:

> ***H1****: The degree of diversity in a firm's technology base has an inverted U-shaped relationship with the quality of its technology portfolio.*

Likewise, extending this notion to the concept of technological relatedness, it is alleged that:

***H2**: The higher the degree of competence-based technological coherence within a firm's technology portfolio, the stronger the positive impact on technological quality.*

Methodology and data

Since both technological competencies and capabilities can only be codified to a limited extend, due to the high level of abstraction of the constructs, adequate proxy measures are needed as indicators for technological diversity and quality. Here, patent applications have become established as the most common measure (Argyres 1996; Patel & Pavitt 1997; Silverman 1999; Cantwell & Piscitello 2000; Fai 2003; Breschi et al. 2003; Stephan 2003; Cantwell & Vertova 2004; Lin et al. 2006; Miller 2006).[7] In order to avoid systematic and procedural biases and ensure decent predictive validity, only patent data from applications at the European Patent Office (EPO) have been included in the sample data. The data set is obtained from PATSTAT (Version Fall 2015).

In order to assess the levels of diversity among individual firms' technology bases, in a first step, a simple entropy measure is adopted, i.e. a continuous inverse concentration measure, weighing each distribution center of dispersion by the natural logarithm of its reciprocal value. [8] Consequently, the degree of technological diversification (DIV) over N technology fields i (i=1…N; N≤35) is calculated as:

$$DIV = \sum_{i=1}^{N} T_i \ln(1/T_i)$$

[7] Patents are found to have a series of advantages over other, especially over input-based, indicators of technological diversification: They ensure a higher content validity due to their broad, public availability over long periods of time and, besides bibliographic references, provide valuable technological content information, through the extensive documentation and the classification into internationally uniform technology fields (Cantwell & Vertova 2004). Moreover, patent applications constitute an even more reliable measure for assessing technological competencies than patents, since, independently from an actual patent grant, they are an undistorted indicator that a firm has acquired near state-of-the-art skills and capabilities in a specific technology field (Breschi et al. 2004). Hence, relying on patent application data significantly increases the construct validity of the indicator.

[8] Entropy measures offers the advantage over Herfindahl-type indices, which is also frequently used in the literature, to be more sensitive and, thus, to allow for a better differentiability of degrees of diversification, especially in the face of relatively small dispersion sizes, e.g. with comparatively small firms. Hence, they appeared more suitable for this analysis given the data consistency of the sample.

Here, T_i constitutes the share of patent applications by a firm in technology field i of the overall applications of the firm. The DIV measure is delimited at the lower bound of the function by 0 (perfect concentration) and at the upper limit by 3,555 (perfectly uniform distribution of patent applications over all 35 technology fields).

Further, the degree of coherent technological diversification is expressed by a two-stage entropy measure (DTR), accounting for knowledge-relatedness and competence-based coherence based on Schmoch (2008). This classification builds upon a total of 3.999 IPC subclasses, which are grouped into technology fields and superordinate technology areas exclusively according to the criterion of technological distance (knowledge-relatedness), regardless of the respective hierarchical assignment in the IPC. The DTR-measure is a continuous diversity measure based on the natural logarithm, as proposed by Jacquemin & Berry (1979). Here, the technology fields (i=1…N; N≤35) in which a firms has filed patent applications are ascribed to the respective higher level technology areas (j=1…M; M≤N; M≤5). Thereto, in a first stage, the degree of technological diversification (DT_j) within the single technology areas is calculated as the distribution of patent applications over the technology fields i within the technology area j:

$$DT_j = \sum_{i=1}^{N} T_{ij} \ln\left(\frac{1}{T_{ij}}\right)$$

T_{ij} constitutes the share of patent applications in the technology field i of the overall applications of all technology fields within the technology area j. Subsequently, in a second stage the overall degree of diversification (DTR) taking into account all technology areas is determined:

$$DTR = \sum_{j=1}^{M} DT_j T_j$$

Here, T_j corresponds to the share of patent applications in the technology area j of the overall applications of the specific firm. The DRT measure is confined at the lower limit by 0 (perfect concentration) and at the upper limit by 2,028 (perfectly uniform distribution of patent applications over all 35 technology fields and 5 technology areas).

Technological quality (QUAL) is operationalized by a composite index comprising six single monovariate indicators, which builds upon an index proposed by Lanjouw & Shankerman (2004). By applying an aggregate and complementary indicator, the conditional variance in patent quality is significantly reduced, providing more precise results than single indicators (ibid; Arts et al. 2013). The QUAL-index comprises the indicators for: 1. *forward citations* in the first 5 years from application, 2. *family size*, 3. *patent claims*, 4. *generality*, 5. *grant lag*, and 6. *backward citations*. The respective indicator values for each patent within the sample data set are obtained from the *OECD Patent Quality Indicators database, February 2016*.[9]

The inverted U-hypotheses are tested on a subset of data on technology and patent portfolios of 90[10] German firms from the industrial engineering and the automotive and vehicle construction industries over 25 years (1984-2008).[11] [12] Table 1 contains on overview of the sectoral distribution of sample firms. Patent data were collected at the consolidated level of the parent firms on a yearly basis in order to enclose relevant (patenting) subsidiaries[13]. The ultimately consolidated subset comprises 62.216 patent applications, including 25.592 subsequently granted patents.

Table 1. Distribution of sample firms by ICB sector and subsector

SECTORS	Freq	SUBSECTORS	Freq
Automobiles & parts	29	Auto parts	24
Construction & materials	3	Automobiles	5
General industrials	2	Commercial vehicles & trucks	11
Industrial engineering	52	Diversified industrials	2
Personal & household goods	4	Heavy construction	3
		Household goods & home construction	4
		Industrial machinery	41
Total	*90*		*90*

[9] Cf. Squicciarini et al. (2013); Note at this point that, while the degree of technological diversification is determined based on patent applications (technology portfolio), the average technological quality relates to the patent portfolio. This shortcut is necessary, since most patent quality indicators are available only for granted patents.

[10] Number of firms to be extended in the data set to be extended in subsequent versions of the paper.

[11] Only patent applications and grants until 2008 are considered in order to allow for an unbiased measurement of forward patent citations.

[12] Industry membership for the parent companies has been determined on the basis of the *WZ 2008* classification of industry branches, which for the purpose of international harmonization efforts is formally based on the international *ISIC (Rev. 4)* classification and on the common European classification *NACE (REV. 2)*. For a better differentiation for analysis, subsequently an allocation of firms to *Industry Classification Benchmark (ICB)* sectors and subsectors based on the declared primary activity of the firms in their annual reports was conducted.

[13] Substantial interest = equity stake ≥ 25 per cent.

Consequently, a truncated regression model is adopted to test the hypotheses H1 and H2. The target variable is the average patent portfolio quality (QUAL), determined as the mean of all patents over the entire period. The included covariates are the linear (DIV) and squared (DIV^2) term of technological diversity and related diversity (DTR, DTR^2) in the technology portfolio, measured again as average over the entire period. In order to control for other factors likely to impact technological capabilities, two control variables are included: 1. the consolidated R&D expenditures per year (R&D), in order to control for size effects, and the general size of the patent portfolio, as a measure for accumulated innovative output (PATENTS), in order to control for experience curve effects. Finally, a series of dummies for ICB sector and subsector membership have been included. Table 2 contains the descriptive statistics for the dependent variable and the covariates in the data set. In order to test for normality, a Shapiro-Wilk test was executed, indicating a presumable normally distributed population for both the dependent and independent variables at the p = .05 level, with the exception of the R&D expenditures (RD) for which the null hypothesis could be rejected at p = .001. Because of their apparently highly skewed distribution over the sample, (natural) logarithmic transformations were adopted for the control variables, in the form of log(R&D) and log(PAT).

Table 2. Descriptive statistics

Variables	Description	Mean	Standard Deviation
R&D	R&D expenditures	266.8	859.2
PATENTS	Size of patent portfolio	286.5	617.8
QUAL	Average patent quality	0.301	0.0239
DIV	Simple/ unrelated technological diversity	1.355	0.559
DTR	Related technological diversity	0.727	0.379

Table 3 contains the coefficients of pairwise correlation between the variables of interest. Surprisingly, the technological quality of the sample firms' patent stocks apparently does not exhibit a significant correlation with either of the covariates. Perhaps, this might link to the existence of a nonlinear relationship between dependent and independent variables (as alleged), while, on the other side (especially for the control variables) this might be due to the small sample size, which obviously impacts the acceptable level of significance. As to be expected, the correlation between diversification and related diversification and their respective squared terms is considerable.

Table 3. Pairwise correlation matrix

	QUAL	R&D	PATENTS	DIV	DIV^2	DTR	DTR^2
QUAL	1						
R&D	-0.0928	1					
PATENTS	-0.1245	0.7916*	1				
DIV	0.0396	0.3329*	0.4127*	1			
DIV^2	0.0055	0.3712*	0.4810*	0.9659*	1		
DTR	0.0167	0.3004*	0.4054*	0.8201*	0.7911*	1	
DTR^2	-0.0412	0.3256*	0.4723*	0.7895*	0.8134*	0.9639*	1

* Indicates significance at .01.

Empirical results

The results of the regression estimations of the relationship of technological capability and diversity are presented in Table 4. As a Breusch-Pagan test showed strong evidence for heteroscedasticity, robust standard errors of regression coefficients are used in all estimated models. Post-estimation, an information matrix test, as proposed by Hall (1987), was carried out as misspecification test for the model, rejecting the latter in all tested directions. Further, in order to test for omitted variables, a joint test of statistical significance of additional variables[14] was executed, rejecting their appropriateness for the model. Finally, in order to test for suspected endogeneity of DTR, a robust Durbin-Wu-Hausman test was executed. According to the test statistic, the regressor is found to be strictly exogenous.[15]

Model 1 includes only the control variables. As already observed for the correlation matrix, the coefficients for R&D expenditures and the size of the patent portfolio are not significant at p= .1. While the coefficient of log(R&D) exhibits the expected positive sign, the size of a firms patent portfolio seems to have a slightly negative impact on its average quality, which might be related to inflative patenting behavior. The fact that both control variables remain insignificant throughout all models is seen as unproblematic, since their theory-validated inclusion reduces the likelihood of inconsistent parameter estimation due to an omitted variable bias, even though this reduces the precision of estimation. In Model 2 and 3, the variables for

[14] Tested additional variables were: consolidated sales volume as a control for size effects and the interaction term between the degree of related diversification and R&D expenditures.

[15] Log(SIZE) was used as instrument. Test-statistic: p = .5996.

simple technological diversity (DIV) and, respectively, coherent technological diversity (DTR), accounting for the knowledge-based relatedness between technology fields, are included in order to first assure that there is indeed no linear relationship between neither of the constructs and the target variable QUAL, which is in fact confirmed, as in neither of the two models the coefficients are significant at at least p = .1.

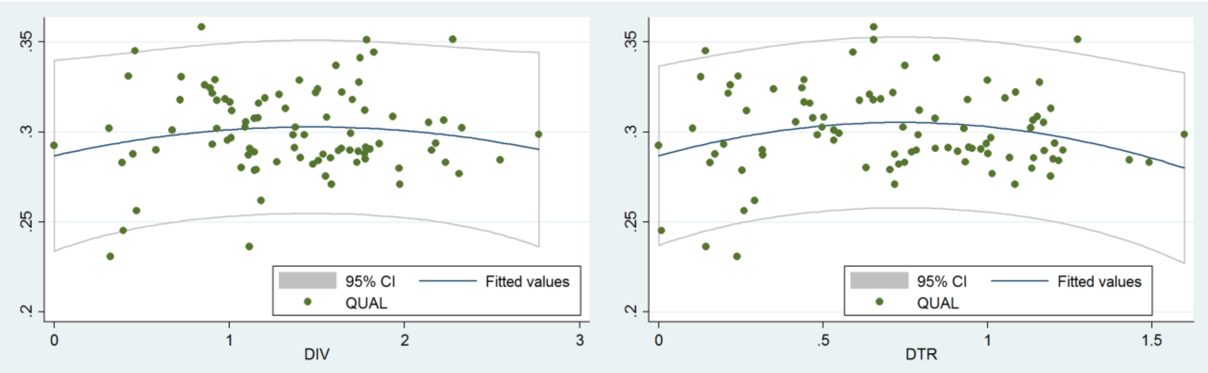
Table 4. Results of cross-section regression analysis of firm technological quality performance (QUAL)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
log(R&D)	.000750	.000325	.000458	.000413	.000261
	(.00234)	(.00225)	(.00227)	(.00286)	(.00261)
log(PAT)	-.00223	-.00240	-.00235	-.00181	-.00166
	(.00278)	(.00283)	(.00283)	(.00298)	(.00292)
DIV		.00365		.0197	
		(.00592)		(.0185)	
DIV^2				-.00634	
				(.00616)	
DTR			.00368		.0544*
			(.00844)		(.0284)
DTR^2					-.0346**
					(.0173)
				(.0135)	(.0141)
constr(2350)				.00162	.00677
				(.0152)	(.0160)
genind(2720)				-.0133	-.0127
				(.0134)	(.0139)
indeng(2750)				-.0138	-.0135
				(.0122)	(.0134)
house(3700)[1]				-	-
Constant	.308***	.305***	.307***	.306***	.302***
	(.00837)	(.00896)	(.00878)	(.0199)	(.0180)
Observations	90	90	90	90	90
lpl	209.112	209.377	209.235	209.916	211.182
Chi-square	1.08	1.27	1.27	2.53	7.61

Robust standard errors in parentheses.
*** Indicates significance at .01.
** Indicates significance at .05.
* Indicates significance at .1.
[1] Dummy house(3700) omitted for collinearity.

In Model 4 the hypothesis H1: The degree of diversity in a firm's technology base has an inverted U-shaped relationship with the quality of its technology portfolio, is formally tested, by including the squared term for (simple) technological diversity. Here, the expected negative sign for DIV^2 is found, but at this point the null hypothesis cannot be rejected, since no significant effect is observed, implying that perhaps there is no inverted-U relationship between the sheer level of diversity in a firm's technology base and the resulting technological quality.

Figure 3. Observed values and fitted regression line of technological quality (QUAL) as a function of technological diversity (DIV) and related diversity (DTR)



In order to account for knowledge-based coherence in the pattern of diversification, in Model 5 the measure for related technological diversity (DTR) as well as its squared term is included instead of DIV, testing for the hypothesis H2: The higher the degree of competence-based technological coherence within a firm's technology portfolio, the stronger the positive impact on technological quality.[16] Here, the expected effect, with the negative coefficient sign for the squared term of diversity, can indeed be observed and is significant at $p = .05$, which is quite remarkable given the small number of observations. This gives support for the assumption that, considering the commonalities and complementarities of the underlying knowledge bases of different technology fields, the marginal effect of increasing diversity in the technology base on technological capabilities is initially positive, but decreases for highly diversified

[16] Obvioulsy, this is econometrically untrue: In this preliminary version of the paper, a reduced cross-section data set is being used, which does not allow for any statistically consistent and valid inference about H2. In order to formally test for the strength of the alleged effect, the adoption of a dynamic (panel data) model and the inclusion of an interaction term between the level of diversity and a firm-specific measure for coherence is needed, requiring longitudinal data, which is intended to be included in a revised forthcoming version of the paper.

firms. Figure 3 depicts a graphical comparison between the plain diversity (DIV) and the coherence-based diversity measure (DTR) for this relationship over the analyzed subset.

Discussion and conclusion

This paper examines the relationship between diversity within the (corporate) technology base and the technological capabilities of firms. Drawing on insights from the broad literature on innovation and managerial economics, which insinuates a rather complex nonlinearity within this context, it is argued that by increasing diversity over a variety of technology fields that rely on common or complementary knowledge firms can improve their technological capabilities by realizing economies of scale and scope in knowledge processes (exploitative dimension). This effect is captured by, e.g., the rate of backward citations, patent claims and the grant lag of patented innovations of a firm. Moreover, it is conceptualized that firms can also improve their dynamic technological capabilities by purposively creating diversity, in order to achieve cross-fertilization and fusion of technology fields, developing more complex innovations that exhibit better absorptive capacity and resilience towards disruptive technological change. In this case, diversity fulfills the function of being a strategy against ignorance, aimed at fostering the dynamic technological adaptability of the firm, thus, addressing the explorative dimension of knowledge-related ambidexterity. The strength of technological capabilities in this regard is captured by, e.g., the index of generality or the amount of forward citations of patented innovations of a firm. It is further argued, that as the level of diversity increases over a certain, firm specific threshold, inefficient exploration prevails and its marginal effect on technological capabilities decreases to become negative, as coordination and integration costs escalate and economies of scope and scale in the knowledge base can no longer be realized, with knowledge-related-ties breaking up. The hypothesis of the outlined inverted-U relationship that is moderated by the level of competence-based coherence has been empirically tested on a subset of 90 consolidated German firms from technology-intensive industries. The results of the econometric model provide strong evidence for the existence of the alleged relationship.

There are a few limitations to this paper and its preliminary findings: On the conceptual level, adopting with technological diversification a concept that has originally been developed at the industry level creates some drawbacks when it comes to accounting for firm exogenous factors. Hence, the multiplicity of actors that determine the evolution of the technology base of an industry as well as spillover and co-creation potentials among industry participants, which strongly impact the development of technological capabilities of single firms within a dynamic setting, could not explicitly be taken into account here. Moreover, here the changing environment is conceptualized as given without further differentiating between different regimes of environmental circumstances, e.g. routinized regimes vs. disruptive or turbulent environments, which might be a promising link for further research in the assessment of technological capabilities. Also the operationalization of technological quality with regards to capabilities might offer substantial potential for further refining. Finally, of course there are still a few econometric limitations, as before mentioned, which restrict the validity and the suitability for extrapolation of the results of this study. These are mostly determined by the small number of observations and the structure of the data subset, having cross-section data not allowing for a proper econometric modelling of the moderating role of the coherence measure. Due to these drawbacks, results from the study, at this stage of work, cannot yet be unconditionally generalized and, hence, do not allow for further or final conclusion at this point.

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