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Managing Portfolio Risk in Strategic Technology Management: Evidence from a Panel Data Set of the World's Largest R&D Performers

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Abstract

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JEL codes: O32, O34

Keywords: patents, financial performance, firms, technology base

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1 Introduction

The ability to offer unique products and services that generate value for their customers is central to companies' success. It is well established that innovation plays an outstanding role in this ability, and innovation has become a self-sustained competition parameter (Schubert 2010). From a theoretical point of view, this has been flagged prominently in evolutionary economics (Nelson and Winter, 1982, Nelson and Winter, 2002) and in the dynamic capabilities literature (Eisenhardt and Martin, 2000, Katila and Ahuja, 2002, Teece et al., 1998, Teece 2007, Yayavaram and Ahuja, 2008).

Empirical evidence on the importance of technology has been gathered by the patent literature. Several studies have demonstrated that firms' technology bases contribute to a better financial performance (Archibugi and Pianta 1996, Griliches 1981, Hall et al. 2005). While these insights are important, the patent literature has expended little effort on disentangling the technology bases, implicitly treating them as homogenous stocks. From the strategic perspective on technology bases, this conceptualization is probably too broad as it suppresses many of the complexities of managing the technology base. In this paper, we argue that a firm's technology base consists of different technologies, whose relations to each other are important.

In particular, we propose to view technology bases as portfolios consisting of individual non-homogenous technologies. We draw on portfolio theory in technology management (Lin and Chen, 2005, Klingebiel and Rammer, 2014), which places risk considerations center stage. Acknowledging that technology development is generally risky, we argue that, through broader technology bases, firms can create hedges that offset commercialization risks occurring when they are active on international markets as well as technological risks.

We base our analyses on a large, international panel dataset combining the DTI-Scoreboard with the Compustat and the PATSTAT database. Using fixed effects regressions for both Tobin's q as a measure of stock market performance and the Return on Assets (ROA) as a measure of profitability, we largely corroborate the predictions of our portfolio-based approach.

2 The economic value of the technology base

2.1 Exposition of the framework

There is a wide range of management and economics literature analyzing how technology contributes to a firm's performance. The patent literature in empirical economics has primarily analyzed whether (and if so by how much) technology measured by patent stocks increases stock market valuations or profitability performance. The most frequently considered characteristics are size of the technology stock (e.g. Chen and Chang 2010, Hall et al. 2005) and its novelty/quality measured using forward citations (Hagedoorn and Cloodt, 2003, Lanjouw and Schankerman, 2004, Trajtenberg, 1990). Another important theme in economics is the role of the commercialization strategy. Cohen and Klepper (1996) and Klepper and Simons (2005) have observed that there are increasing returns to technology development because the associated costs are largely fixed and thus independent of firm size. A corollary is that firms should commercialize their technologies in as many markets as possible (see Lanjouw et al. 1998, Fischer and Leidinger, 2013).

Mostly, the patent literature has equated technology bases with technology stocks, which is not just a semantic change but is indicative of the implicit assumption that the technology stock is homogenous and can adequately be represented by average characteristics, e.g. average novelty measured through average number of received forward citations).

Studies in strategic management and evolutionary economics, however, have tried to disentangle the technologies/knowledge available to the firm, following the idea that the source of innovation is actually a recombination of different kinds of technologies and the knowledge incorporated in them (Fleming 2001). This line of research has, for example, focused on the optimal distance of technologies within the knowledge base (Yayavaram and Ahuja, 2008), or on the role of variety and diversity in the knowledge base (Colombelli et al. 2014, Ghapar et al. 2014). The distinctive feature of this research is that it regards the technology base as consisting of individual technologies, whose interactions play a significant role

We argue that this change of focus has important implications. If a technology base consists of different technologies whose relations to each other are important, a portfolio approach appears most suitable. Such a framework, although not systematically applied in the patent literature, is quite common in technology management, where the portfolio approach has been used to argue that large technology portfolios can perform a risk-spreading function (Kfir 2005, Klingebiel and Rammer, 2014).

This suggests that greater technological breadth in a portfolio can offset the various risks associated with technology development, for example those related to the commercialization strategy (in particular in terms of market reach).

By combining the insights of patent economics into size/novelty and market reach of the technology stock with the portfolio approach that is most prominent in technology management, the aim of this paper is to show how technological breadth as a hedge against risk affects the impact of size/novelty/market reach on firm performance, which has previously been analyzed primarily within a deterministic framework. Before we describe these ideas more clearly, we start with a brief review of the existing literature.

2.1.1 Size and novelty of the technology base

In the patent literature, the relation between the size of the technology base, measured by the number of patent filings or patent grants, and the novelty of the technology base, mostly measured by received citations, is well established. The argument is not only that large patent portfolios indicate greater R&D efforts and therefore a higher innovative output (Griliches 1978, Griliches, 1990). Large patent portfolios are also strategically useful, for example, to block competitors or prevent them from entering relevant markets and to increase the chance for licensing agreements or trade with other firms (Blind et al. 2006). Furthermore, a large patent output can be interpreted as a positive signal to the market. Theoretically, higher stock market prices are justified from a capability-oriented view by the expectation that firms commanding more novel technology bases may not only capitalize on products that offer value to customers, but also have revealed an ability to change their technology base and are thus more able to adapt in the face of changing environments, such as changing consumer demands or the emergence of new technologies (Teece 1998, 2007).

In line with these arguments, empirical evidence on the positive effect of the size of the technology base on market valuation has been gathered by Chen and Chang (2010), Deng et al. (1999), Griliches (1981), and Hall et al. (2005).

As concerns novelty, the citations a patent receives from subsequent patents, i.e. patent forward citations are a widely used indicator (Narin et al. 1987; Trajtenberg 1990). It is assumed that the number of forward citations measures the degree to which a patent contributes to further developing advanced technology, which can be seen as an indicator of technological significance (Albert et al. 1991; Blind et al. 2009; Carpenter et al. 1981).[1] Studies that provide empirical evidence for a positive effect of novelty on firm performance include Narin and

1 As a specific feature of the EPO, patent citations are categorized into different types. First of all, there are citations which are particularly relevant regarding the assessment of the novelty or the inventiveness of the application (invention) examined. These can be termed the "relevant" citations with the codes X or Y. We assumed that X or Y citations exert a different influence on measures of firm performance than using forward citations in general. Analyzing the correlations, however, revealed that X and Y citations are closely correlated with forward citations in general. Therefore, no distinction is made for X and Y citations in the following analyses for multicollinearity reasons.

Noma (1987), Hagedoorn and Cloodt (2003), Lanjouw and Schankerman (2004), Hall et al. (2005) and Trajtenberg (1990).

2.1.2 Market reach of the technology base

Originally, Klepper and Cohen (1996) and Klepper and Simons (2005) argued that the costs of creating a technology are largely fixed. Thus, if the resulting product can be applied to a larger sales base, the per-sales-unit costs decrease, implying increasing returns to scale in the commercialization of a technology. Given that a firm already possesses a technology, it should therefore seek to commercialize it as broadly as possible. In terms of patenting, this means that firms can realize higher returns from their technologies if they target not only the domestic, but also foreign markets. A larger family size (i.e. the number of countries a patent is applied in) should thus increase the financial performance of firms. In line with this argument, several authors have shown that large patent families are an indicator of the quality of the patent portfolio and that (auction) prices of patents increase with family size (Putnam 1996, Lanjouw et al. 1998, Fischer and Leidinger, 2013)

2.1.3 Risk of the technology base

Because the patent literature has treated patent stocks as largely homogenous, characterizing them using structural features like size/novelty or market reach, it has ignored risk assessments that are an important topic in technology management literature (Crawford 1987, Urban/Hauser 1993). Following insights from portfolio theory, the main proposition is that firms should not regard their technologies in isolation, but as a portfolio (Kfir 2000, Lin and Chen 2005, Sharma et al. 2009, Wooje et al. 2013). The decisive aspect of the portfolio idea is that it may act as a “hedge” against risks, because even if one technology fails, another in the portfolio might succeed (Abernathy/Rosenbloom, 1968, Klingebiel and Rammer, 2014). Firms with limited portfolios might easily end up in a situation where their few projects fail, resulting in serious threats to their very existence. This can be due to technological risks as reflected in the literature about parallel research (e.g. Eisenhardt/Tabrizi 1995, Pich et al. 2002) or demand side or market risks (Abernathy/Utterback 1978). Such demand-side risks may stem from many sources such as incomplete knowledge about future events, consumer preferences, and institutional issues.

Based on the preceding discussion, one conclusion from the literature regarded is that firms profit from larger and more novel technology bases, which they should commercialize as broadly as possible in order to reap returns to scale. At the same time, they should seek to minimize risks in their technology portfolios, which is heavily influenced by the breadth of the technology portfolio. We summarize this in our baseline hypothesis.

H1: Greater size/novelty, higher market reach, and greater technological breadth increase a firm's financial performance.

2.2 The interrelations between size/novelty, market reach, and risk

Problematic about H1 is that it can hardly be assumed that the objectives listed therein can be achieved independently of each other. In particular, increasing market reach is likely to induce additional risks, especially if the firm is not well acquainted with the specificities of foreign markets (Ceci and Prencipe, 2013, Baier et al., 2015). Furthermore, although a novel technology base can provide important competitive advantages, it is likely that the limited degree of codification of knowledge in novel technologies induces additional risks and uncertainty (Law, 2014).

Thus, in order to better understand how firms can strategically manage the trade-offs between these objectives, we need to analyze how they interact. This will be done in the following.

Because risk considerations are at the core of this paper, we also differentiate two indicators of financial performance that have often been used interchangably: Tobin's q and Return on

Assets. We argue that Tobin's q is a capital market measure, which also reflects investors' and managers' risk preferences (Lambrecht and Myers, 2008, Admati et al. 1994). The ROA, on the other hand, results from the firm's actual operations on its market and therefore should be less responsive to changes in risk.

As already argued, the portfolio approach to technology management stresses the role of managing technologies to reduce risks. Firms should regard their different technologies as a portfolio and not in isolation (Kfir 2000, Lin and Chen, 2005). There are two lines of argumentation that relate the properties of the portfolio to the overall risk to the firm's business. The first is a statistical approach that claims that, in broader technological portfolios, the failure of one project can be offset by success in another (Abernathy/Rosenbloom, 1968). Klingebiel and Rammer (2014) have provided evidence for this on the innovation project level.

The second perspective is evolutionary and starts from the observation that firms which are technologically more diverse are more innovative and have higher survival chances (Breschi et al. 2003, Garcia-Vega, 2006, Oostergard et al. 2011). This approach contends that new knowledge results from recombining old knowledge to a large degree (Yayavaran and Ahuja, 2008). Firms that can access a bigger pool of knowledge are more able to create new knowledge flexibly as needed (Fleming 2001). In this respect, firms with a broader technology base that reflects greater knowledge variety have a bigger chance of adapting their technology base by recombining knowledge should some of their technologies fail on the market (Colombelli et al. 2014, Lin and Chang, 2015).

2.2.1 Size/novelty and technological breadth

Innovation is seen as an unpredictable process which carries considerable technological uncertainty for firms. Law (2014) distinguishes two sources of technological uncertainty: component ambiguity (i.e. not understanding what a knowledge asset contains) and causal ambiguity (limited understanding of what a knowledge asset is good for). Thus, larger technology bases are also likely to be associated with additional risks and uncertainties, constituting a greater need for risk management through diversification. This effect could be even stronger for more novel technologies. Accordingly, Katila and Ahuja (2002) find that very novel technologies are on average of lower value than more incremental technologies, yet the variance in the value distribution is higher. This is primarily because the technologies are not fully understood and the ways of dealing with them and manipulating them are often subject to inductive rather than standardized and deductive approaches (Abernathy and Utterback 1978, Arora 1997). While highly novel technology bases increase the chances of generating very high profit streams, the above insight suggests that firms will be worse off on average unless they are able to control these kinds of risks. As Loch et al. (2001) describe it in their formalized model of parallel research, firms should emphasize "selectionist strategies", which refer to any strategy that allows alternative technological candidates to compete in order to arrive at the optimal solution, when the technological terrain is not or only poorly known.

Following these arguments, we posit that firms with a larger technology bases and a higher degree of novelty in their technology bases should have broader technology portfolios because of their inherent inability to fully foresee future developments. The underlying argument is that of hedging risks as used before to derive the risk-mitigating effect of greater market reach.

H2a: The larger/more novel the technology base, the more financial performance is affected by the breadth of the technology portfolio.

As argued above, the effects might depend on the choice of financial performance measure. A primary source of divergence between the commonly interchangeably used ROA and Tobin's q, however, stems from the fact that the latter (as a measure of the market expectations about the firm's future performance) also reflects investors' preferences. In particular, if uncertainty comes into play, risk aversion suggests that the positive effect of a technological hedge against risk will be reflected more strongly in Tobin's q than in the ROA, which (as the de facto outcome of a firm's contemporaneous market operations) is independent of investors' risk preferences.

H2b: The moderating effect of the breadth of the technology portfolio with regard to size/novelty is stronger for Tobin's q than for ROA.

2.2.2 Market reach and technology breadth

While earlier research argued that more internationalized firms possess risk advantages because of their market portfolio advantages (Hughes et al. 1975), more recent studies have suggested that internationalization is associated with greater risk. The reason is that the positive effect of non-perfectly correlated markets might be overcompensated by an increase in the variance of the profit flows in each individual market (Reeb et al. 1998). The reasons for this vary widely and may be related to exchange rate volatility (Bartov et al. 1996) or limited knowledge about foreign markets and their institutional framing, for example, regulatory issues (see e.g. Kwok and Reeb, 2000). This can also extend to a limited ability to understand local preferences and consequently to correctly anticipate demands for a certain technological solution (Baier et al. 2015). Such risks might be reduced if the technology set is broad, in particular, if the risk increases due to increased market reach are independent of the technology that is applied. While this might not be true for technological regulation on foreign markets (because broader technology bases will inflate the need for in-depth knowledge about the regulations), it is much more likely for all risks that relate to exchange rate volatility, or institutional or law differences affecting business operations in general. The risk reduction argument can also be very important in the case of incomplete knowledge about consumer preferences in foreign markets, because the ability to offer technological alternatives can reduce the risk of misjudgments.

H3a: The breadth of the technology portfolio positively affects a firm's financial performance, in particular if the technology base has a high market reach.

With a similar argument as in H2b, we can conclude with the following hypothesis.

H3b: The moderating effect of the breadth of the technology base concerning market reach is stronger for Tobin's q than for ROA.

3 Data and methods

3.1 The data

For the empirical analysis, a panel dataset including 479 firms from 1990 to 2007 based on the DTI-Scoreboard[2] was constructed that contains data on R&D expenditures, market capitalization, turnover etc. The base year for the construction of the dataset is 2001. A total of 500 companies were listed in the DTI-Scoreboard for this year. Company data from the previous and following years were added to this dataset to construct a firm-level panel. If any company was not listed in the years before or after 2001, the respective observations were treated as missing. This implies that our dataset has the form of an unbalanced panel.

In the case of mergers and acquisitions (M&A) between listed companies, the data of the respective companies were added for the entire time period. The companies were thus treated as if they were already merged at the beginning of the observation period.[3] M&A with

2 The DTI-Scoreboard is an annual ranking of firms alongside their R&D expenditures. Initially, it was published by the UK's Department of Trade and Industry (DTI). The most recent version of the Scoreboard was published by the UK Department for Business, Innovation and Skills (BIS). However, the service for the DTI-Scoreboard was discontinued in 2012. The versions used to create the dataset for this analysis can be accessed at the UK government's National Archive: http://webarchive.nationalarchives.gov.uk/20101208170217/http://www.innovation.gov.uk/rd_scoreboard/?p=31

3 This preserves comparability over time, as it is no longer possible to separate the individual company information after a merger (compare Frietsch, 2006).

companies not listed in the DTI-Scoreboard had to be left uncontrolled.[4] Since the DTI-Scoreboard is a ranking of companies according to their annual R&D expenditures, large firms are overrepresented in the sample. A brief overview of the size- and country-specific distribution of the firms across countries can be found in Tables A-1 and A-2 in the Annex.

The relevant patent data were extracted from the 'EPO Worldwide Patent Statistical Database' (PATSTAT), which provides information about published patent documents collected from 83 patent authorities worldwide. We restricted the analyses to EPO data in order to focus on a consistent and homogeneous patent system. All patent data reported are dated by their priorities, i.e. the year of world-wide first filing.

The companies in the patent data were identified via keyword searches. The keywords also included the names of the subsidiaries which were held by the parent company with a direct share of at least 25% to keep the patent data comparable with companies' financial information. Information on the names of the relevant subsidiaries was taken from the LexisNexis (http://www.lexisnexis.com) and Creditreform Amadeus (http://www.creditreform.com) databases. The subsidiary information was collected at one specific point in time. The companies plus their subsidiaries were then treated as such for the entire observation period.

The financial data needed to calculate the companies' financial performance indicators were taken from Standard & Poor’s COMPUSTAT Global and COMPUSTAT North America databases.

We restricted our sample to firms from the manufacturing sector according to the North American Industry Classification System (NAICS). All firms belonging to NAICS 2-digit groups 31, 32 or 33 were coded as belonging to this sector. Since the data to construct the

4 In any case, since this contains the most important R&D performers, the enterprises not listed should be smaller and distortions should be correspondingly limited.

Tobin's q variable are only available from the year 2000 onwards, all further analyses are additionally restricted to the years 2000 to 2007. Our final sample thus consists of 2,854 observations from 367 firms in total. The number of observations and firms are lower in the given regression models due to missing values for some variables.

3.2 Variables

3.2.1 Market value and profitability

We use Tobin's q as a measure of financial market performance. Since the calculation of Tobin's q is complicated and data-intensive, we use the approximation suggested by Chung and Pruitt (1994). In their application to the manufacturing sector, they show that this simplification explains at least 96.6% of the variability of Tobin's q. The formula, calculated for each company and year, is as follows (time and company subscripts are omitted for the sake of simplicity):

$$q = \frac{((SO * SP) + PS + (LC - AC) + LD)}{AT} \qquad (1)$$

where q denotes the approximate version of Tobin's q, SO the number of outstanding shares of a firm and SP the share price. The latter two together form the market capitalization of a firm. PS is the firm's preferred stock, LC its current liabilities, AC its current assets and LD its long-term debt. Everything is divided by AT, the company's total assets.

To assess the profitability of a company, we focus on the return on assets (ROA). This measures contemporaneous profitability relative to the asset base that was used to generate the profits. It is formally defined as earnings before interest and taxes $EBIT$, divided by the total assets AT of a company:

$$ROA = \frac{EBIT}{AT} \qquad (2)$$

3.2.2 Explanatory variables – the patent indicators

Now turning to the patent-related measures, several variables were generated in order to test our hypotheses. We begin with the size of the technology base of a firm, calculated as the number of EPO patent applications divided by total assets (in millions) per firm and year. As such, this is a (relative) quantity measure of the size of the technology base.

The novelty of a firm's technology base is captured by the ratio of the average number of forward citations (in a four-year time window) to the average number of backward citations per company and year. There are two reasons for defining this measure like this: First, forward citations are interpreted as a measure of technological significance that is usually also related to novelty. Numerous studies have also shown a relation of this measure to patent value (Gambardella et al. 2008, Harhoff et al. 2003, Schubert 2011, Trajtenberg 1990) and stock market values (Albert et al. 1991, Deng et al. 1999, Hall et al. 2005). Furthermore, backward citations usually indicate a stock of existing knowledge that the patent draws on (Rosenkopf/Nerkar 2001). Thus, in parts, they represent incremental improvements. If, as a measure of reuse in future technologies, forward citations are high (indicating basicness or novelty) and backward citations are low (indicating incrementalism), then the patent is likely to protect a newer or more radical technology.

For our technology breadth measure, we calculated the difference between the average number of 4-digit IPC classes a company's patents are classified in and the mean average number of 4-digit IPC classes normalized by country, sector (NAICS-level-3) and year. To account for the fact that this indicator might turn negative, which would render its interpretation more difficult when it comes to the interactions, we transformed it by subtracting the mean and adding the minimum value, implying that this variable can only take on values equal to or above zero. By using this normalized measure, we are able to control for possible sector-, country- and period-specific biases in the IPC classification.

We follow a similar approach with respect to the market reach of the technology base. Here we use the difference between the average family size of a company's patent portfolio and the mean average patent family size by country, sector and year. Alongside the calculation of the technological breadth variable, we applied the same transformation so that the variable can only take on values equal to or above zero. The family size is determined by the number of distinct patent offices at which a patent application has been filed. Yet, it can be argued that the family size of a patent is also dependent on the firm's evaluation and goals with the patented technology, i.e. it might be linked to the quality of a patent (Van Zeebroeck 2011). The argument is that a patent is filed more frequently in foreign jurisdictions if the patented invention is assumed to be of high quality, which reflects the argument made by Putnam (1986) as well as by Harhoff (2003), who stated that more valuable inventions generate larger patent families. In order to control for this effect, we always use both measures – novelty and family size – simultaneously in our regression models. In any case, we find a rather low, yet significant, bivariate correlation of 0.04 when correlating our novelty measure with the market reach measure.

Table 1: Summary statistics

Variable Name	**Abbrev.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**	**Groups**
Tobin's q	Tobin's q	1.42	3.26	0	100.54	2629	358
ROA	ROA	0.08	0.08	-0.64	0.4	2852	367
EPO Appl./Total Assets	Pat. size	0.02	0.05	0	1.01	2568	354
Forward Cit./Backward Cit.	Novelty	0.16	0.19	0	4.2	2563	354
Market reach: Family Size	Market reach	12.375	1.3942	0	24.75	2563	354
Tech. Breadth: IPC	Tech. breadth	2.6289	0.32	1.381	6.7949	2570	354
R&D/Sales	R&D/Sales	0.08	0.09	0	0.96	2701	366
Sales/Employees	Sales/Emp	0.2	0.12	0.04	0.98	2601	360
Intangible Assets/Employees	Intan/Emp	38.44	93.6	0	1961.78	2722	362
EBIT/Employees	EBIT/Emp	21.12	41.81	-371.98	548.85	2784	364
Capital Expenditures/Employees	CapEx/Emp	11.83	13.28	0	154.57	2766	363
Long-Term Debt/Employees	Debt/Emp	39.71	58.95	0	989.87	2781	364
Sales	Sales	9922.15	18460.69	56	184879	2707	366

We include several control variables with respect to potentially confounding firm characteristics in addition to the patent indicators discussed above. Company sales (in millions) are included to control for size effects. We also include the square of sales to allow for non-linear effects. To account for the firm's productivity, we use sales (in millions) per employees (in thousands). To control for R&D input, we use a firm's current R&D intensity (R&D expenditures in millions divided by sales in millions) as well as its R&D intensity in the preceding year to additionally account for delayed effects, as R&D is usually an investment that takes time to create value. We further control for the share of intangible assets, earnings before interest and tax (EBIT), long-term debt and capital expenditures (all in millions per thousand employees). In all of our models, we also include time-dummies to control for period-specific effects. An overview of the variables including summary statistics can be found in Table 1.

4 Estimation methods

In order to test the hypotheses, we performed fixed effects (FE) panel regressions to allow for individual effects to be correlated with the error term. If models are subject to unobserved heterogeneity which is correlated with the explanatory variables, pooled OLS or random effects estimators are inconsistent. Since we believe that firm-specific effects will be highly relevant, the fixed effects estimator is best suited to eliminating unobserved heterogeneity. We also employed a Hausman Test, which showed that the random effects assumption (i.e. that explanatory variables are uncorrelated with company-specific effects) is violated. The linear panel data model is as follows:

$$y_{it} = x_{it}\beta + c_i + u_{it} \qquad i = 1, ..., n \qquad t = 1, ...T \tag{3}$$

where y_{it} is the explained variable of unit i in period t, x_{it} is a vector of explanatory variables, β is a coefficient vector, and c_i is a company-specific effect potentially correlated with idiosyncratic errors u_{it}.

To control at least partly for any remaining sources of endogeneity in our models, we re-run all the models with the same specifications but with the one-year lagged versions of all explanatory variables. This is to make sure causality runs from the patent indicators to the financial performance measure and not vice versa.

As concerns the interactions between the size of a firm's technology base, its novelty, its breadth and its market reach, we run several sets of additional models including those interaction terms.

5 Multivariate results

Table 2 presents the results from the first set of FE regressions on Tobin's q and ROA.[5] Before we look at the interaction effects in more detail, which form the core of our analyses, we briefly discuss the main effects of our measures as hypothesized in H1.

In Table 2, we observe a significantly positive effect of the variable capturing the size of the technology portfolio on Tobin's q (M1-1 and M1-2). A positive and highly significant effect can also be observed for the variable capturing the novelty of the technology base. Thus, we can state that the stock market does reward firms with a more novel technology base, which is in line with findings from the existing literature (e.g. Chen and Chang 2010, Deng et al. 1999, Griliches 1981, Hall et al. 2005). It is also in line with Teece’s (1998, 2007) arguments concerning the competitive importance of innovation in the construction of dynamic capabilities and value. Yet, not only Tobin's q, but also ROA is positively affected by the size and novelty of the technology base, although the effect of both variables on the ROA is less pronounced (M1-3 and M1-4).

The market coverage also positively influences Tobin's q (M1-1 and M1-2) and firm profitability (M1-3 and M1-4). Here, we argued that a broader set of targeted markets leads to a larger consumer base, which is a necessary precondition to recouping the costs of technology development.

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5 Industry-specific effects are absent from the models, because they are eliminated by using the fixed effects estimator. This does not mean that they remain uncontrolled. Rather, they simply cannot be identified.

Finally, the breadth of the technology base, as a hedge against risk, also influences market value positively (M1-1 and M1-2). On the basis of portfolio theory, we argued that this is because the firm itself is not critically endangered if one of its patented technologies fails, since it still has other technologies in its portfolio. However, we find the effect is not significant regarding the ROA (M1-3). Yet the coefficient is significantly positive when looking at the lagged variable (M1-4).

Table 2: Regression results I – basic estimates

	Tobin's q				**ROA**			
	M1-1		M1-2		M1-3		M1-4	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Pat. size	2.926**	1.177			0.313***	0.056		
Novelty	0.874***	0.106			0.015***	0.003		
Market reach	0.043***	0.015			0.002***	0.001		
Tech. breadth	0.113**	0.050			0.004	0.003		
L1.Size			6.879***	1.229			0.376***	0.056
L1.Novelty			0.500***	0.092			0.019***	0.003
L1.Market reach			0.056***	0.014			0.002***	0.001
L1.Tech. Breadth			0.044***	0.050			0.005*	0.002
R&D/Sales	0.802	0.586	0.523	0.576	-0.149***	0.024	-0.181***	0.024
L1.R&D/Sales	2.201***	0.502	1.744***	0.475	0.008	0.020	0.021	0.019
Sales/Emp	2.240***	0.371	2.253***	0.360	-0.056***	0.016	-0.044***	0.015
Intan/Emp	-0.004***	0.000	-0.004***	0.000	0.000***	0.000	0.000***	0.000
EBIT/Emp	0.004***	0.001	0.003***	0.001	0.002***	0.000	0.002***	0.000
CapEx/Emp	0.001	0.002	0.001	0.002	0.000	0.000	0.000	0.000
Debt/Emp	-0.002***	0.001	-0.002***	0.001	0.000***	0.000	0.000***	0.000
Sales	0.000***	0.000	0.000***	0.000	0.000	0.000	0.000	0.000
Sales (squared term)	0.000**	0.000	0.000**	0.000	0.000	0.000	0.000	0.000
Constant	YES		YES		YES		YES	
Time-Dummies	YES		YES		YES		YES	
Number of Obs.	2107		2160		2804		2854	
Number of Groups	332		336		340		344	
R^2 Within	0.291		0.291		0.595		0.601	
F	36.02		37.02		170.55		178.64	
Prob > F	0.000		0.000		0.000		0.000	

Significance Level: ***p<0.01, **p<0.05, *p<0.1

Note: The difference in the number of observations can be explained by the fact that we use an unbalanced panel, in which data could be missing for some observations in the respective years. L1. means that the variable is lagged by one year.

In sum, we can confirm H1. Greater size, greater novelty, higher market reach, and greater technological breadth all increase firms' financial performance. This is in line with comparable results from previous studies in the existing patent literature (e.g. Chen and Chang 2010, Deng et al. 1999, Griliches 1981, Hall et al. 2005, Hagedoorn and Cloodt, 2003, Harhoff et al., 2003, Lanjouw and Schankerman, 2004, Trajtenberg, 1997).

Table 3: The interaction effects on Tobin's q

dV: Tobin's q	**M2-1**		**M2-2**		**M2-3**	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Pat. size	2.660**	1.168	3.639***	1.183	2.633**	1.173
Novelty	0.586***	0.117	0.859***	0.105	0.821***	0.106
Market reach	0.036**	0.015	0.039***	0.015	0.033**	0.015
Tech. breadth	-0.092	0.062	-0.021	0.059	0.110**	0.050
Interaction: Novelty*Tech. breadth	1.015***	0.183				
Interaction: Pat. size*Tech. breadth			10.484***	2.444		
Interaction: Market reach*Tech. breadth					0.127***	0.029
R&D_Sales	0.751	0.582	0.778	0.584	0.784	0.583
L1.R&D_Sales	2.228***	0.498	2.189***	0.499	2.187***	0.499
Sales_Emp	2.262***	0.368	2.202***	0.369	2.201***	0.369
Intan_Emp	-0.004***	0.000	-0.004***	0.000	-0.004***	0.000
EBIT_Emp	0.003***	0.001	0.004***	0.001	0.003***	0.001
CapEx_Emp	0.001	0.002	0.001	0.002	0.001	0.002
Debt_Emp	-0.002***	0.001	-0.002***	0.001	-0.002***	0.001
Sales	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Sales (squared term)	0.000**	0.000	0.000**	0.000	0.000**	0.000
Constant	YES		YES		YES	
Time-Dummies	YES		YES		YES	
Number of Obs.	2107		2107		2107	
Number of Groups	332		332		332	
R^2 Within	0.303		0.298		0.299	
F	36.356		35.524		35.622	
Prob > F	0.000		0.000		0.000	

Significance Level: ***p<0.01, **p<0.05, *p<0.1
Note: L1. means that the variable is lagged by one year.

We now turn to the interaction effects which form the core of our analysis (Table 3 and Table 4).[6] We hypothesized that the size and the novelty of the technology portfolio positively interact with the patent portfolio's ability to hedge against risks due to its technological breadth (H2a) and that the effect is more strongly pronounced for Tobin's q than for ROA (H2b). Indeed, we find a positive interaction effect between the technology portfolio’s novelty (M2-1 and M3-1) and size (M2-2 and M3-2) and technological breadth. This confirms H2a. A large and/or novel technology portfolio, with an inherent inability to fully foresee future developments, should be combined with a strategy of a broad technology to hedge against risks. To find evidence for or against H2b, we additionally calculated the elasticities of the interaction effects on Tobin's q and ROA (Table 5). As we can see, the elasticities are much larger in the case of Tobin's q than for firm profitability, i.e. a one percent increase in the interaction of

6 We have decided to only use the lagged versions of the variables in the ROA models with the interaction effects, since considering a time lag has been shown to lead to more pronounced effects on firm profitability in the previous models.

novelty and technological breadth leads to a 0.33 percent increase in Tobin's q, while this increase is only about 0.11% in ROA. Similar effects can be observed for the other interaction effects, with the difference between the increase in Tobin's q vs. ROA is highest for the interaction between market reach and technological breadth. Consequently, we can confirm H2b. Risk aversion suggests that if uncertainty comes into play, the positive effect of a technological hedge against risk is more strongly reflected in Tobin’s q than in the ROA, which is independent of individual preferences and just resembles a de facto outcome of a firm’s contemporaneous market operations.

Table 4: The interaction effects on ROA

dV: ROA	**M3-1**		**M3-2**		**M3-3**	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
L1.Pat. size	0.368***	0.056	0.358***	0.057	0.372***	0.056
L1.Novelty	0.016***	0.003	0.019***	0.003	0.019***	0.003
L1.Market reach	0.002***	0.001	0.002***	0.001	0.002**	0.001
L1.Tech. breadth	0.001	0.003	0.000	0.003	0.005*	0.002
L1.Interaction: Novelty*Tech. breadth	0.013**	0.006				
L1.Interaction: Pat. size*Tech. breadth			0.330***	0.110		
L1.Interaction: Market reach*Tech. breadth					0.002	0.001
R&D/Sales	-0.186***	0.024	-0.183***	0.024	-0.183***	0.024
L1.R&D/Sales	0.019	0.019	0.023	0.019	0.023	0.019
Sales/Emp	-0.045***	0.015	-0.045***	0.015	-0.045***	0.015
Intan/Emp	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
EBIT/Emp	0.002***	0.000	0.002***	0.000	0.002***	0.000
CapEx/Emp	0.000	0.000	0.000	0.000	0.000	0.000
Debt/Emp	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Sales	0.000	0.000	0.000	0.000	0.000	0.000
Sales (squared term)	0.000	0.000	0.000	0.000	0.000	0.000
Constant	YES		YES		YES	
Time-Dummies	YES		YES		YES	
Number of Obs.	2854		2854		2854	
Number of Groups	344		344		344	
R^2 Within	0.602		0.603		0.602	
F	170.981		171.482		170.761	
Prob > F	0.000		0.000		0.000	

Significance Level: ***p<0.01, **p<0.05, *p<0.1
Note: L1. means that the variable is lagged by one year. The patent indicators and interaction terms were always used in a one-year lagged version in the ROA models

Furthermore, we hypothesized in H3a that there is a positive interaction between the breadth of the technology portfolio and market reach with respect to Tobin's q and firm profitability. The basic arguments are that broader technological portfolios can offset the failure of one project by success in another (Abernathy/Rosenbloom, 1968) and that technologically diverse companies are more innovative and have higher survival chances (Breschi et al. 2003, Garcia-Vega, 2006, Oostergard et al. 2011), i.e. firms with a broader technology base are better able to adapt their technology base to market-related risks.

Table 5: The elasticity of the interaction effects in percent at means

Interaction Term	Tobin's q			ROA		
	Model	Coef.	S.E.	Model	Coef.	S.E.
Interaction: Novelty*Tech. breadth	M2-1	0.3275***	0.059	M3-1	0.1052**	0.049
Interaction: Pat. size*Tech. breadth	M2-2	0.3635***	0.085	M3-2	0.1907***	0.064
Interaction: Market reach*Tech. breadth	M2-3	3.2822***	0.737	M3-3	0.6768	0.412

Significance Level: ***p<0.01, **p<0.05, *p<0.1
Note: The interaction terms were always used in a one-year lagged version in the ROA models.

A patent portfolio that hedges against risks thus becomes even more important when patenting in several jurisdictions. The effects for these interactions on Tobin's q and ROA are shown in M2-3 and M3-3 (Table 3 and Table 4), respectively. As we can see, the interaction effects between the market reach and the breadth of the technology base are significantly positive in the case of Tobin's q. With regard to the ROA, however, we find the interaction effect to be insignificant. Thus, we can only partly confirm hypothesis H3a. A broad technology base becomes more important when combined with a high market reach, but only concerning market expectations about future performance (Tobin's q), not for firm profitability (ROA). With regard to H3b, where we stated that the moderating effect of the breadth of the technology base concerning market reach is stronger for Tobin’s q than for ROA, we see that the elasticity is much higher in the case of Tobin's q than for ROA (where we have to keep in mind that the coefficient for the interaction effect is insignificant). This finally confirms H3b.

6 Discussion & conclusions

Most of the previous empirical patent literature has tried to establish that financial markets reward firms’ investments in their patent stock. Mostly, the focus of these analyses was on identifying the impact of either size of the knowledge stock or its novelty (or potentially some combination thereof, e.g. when analyzing quality-adjusted patent stocks). While this literature has succeeded in demonstrating the high economic importance of investments in knowledge and technology from the perspective of the firm, it has largely ignored that technology bases are not monolithic, but consist of a set of technologies whose interdependencies are important. Using a portfolio approach, we proposed that these interdependencies are crucial to managing risks.

On a theoretical level, we have therefore contributed to extending the mainly deterministic lines of argumentation in patent economics to a broader framework, in which risk considera-tions play a role. We did this by incorporating insights from portfolio theory in technology management into the patent literature.

Furthermore, we have argued that technological breadth can function as an implicit hedge against both technological- and market-based risks. This argument is similar to theories in evolutionary economics and strategic knowledge management which regard technological breadth as a source of diversity that allows firms to recombine knowledge (Fleming 2001) and thus contributes to firm performance (Colombelli et al. 2014). Although the arguments that breadth as a hedge against risk and breadth as a source of diversity appear to differ, we regard them as complementary because the impacts of knowledge diversity on firm performance are usually assumed to be channeled through processes that are not independent of risk, e.g. when resulting knowledge assets bestow a competitive advantage and thus improve the chances of the firm’s survival.

From a practical point of view, we provided evidence that goes beyond the statements that larger or more novel technology stocks are valuable to firms. In particular, we were able to confirm that market reach is indeed a driver of financial performance pointing at the existence of increasing returns to market size. It follows from Cohen and Klepper (1996) that, given the existence of a technology, firms should increase their sales base, which could be achieved by commercializing the technology as broadly as possible. However, increasing market reach does not come without cost, which is also manifested in the form of increased risk.

In this context, we argued that, under such a portfolio perspective, a salient feature of the technology stock becomes apparent - its ability to provide hedges against both technological risks and market risks (Klingebiel and Rammer, 2014, Abernathy/Rosenbloom, 1968). Based on this, the second aim of this paper was to analyze the interrelations between size/novelty, market reach, and risk. Our central tenet was that, although increasing size/novelty and market reach should lead to higher financial performance, both include an element of risk. This is because larger and, in particular, more novel technology stocks bear considerable uncertainties because of knowledge ambiguity. The same holds for the penetration of foreign markets, where additional demand-side risks, regulatory, institutional or legislative risks can emerge. Building on this notion, we argue that, because a broader technology stock can hedge against risks, the increase in financial performance resulting from broader market reach or larger/more novel technology stocks is higher if the technology stock is broader, implying a call for diversification.

Our results not only provide insights for the patent literature, which usually tries to measure the value of investments into technology. This literature therefore implicitly takes an ex ante perspective. We also contribute to the appropriability literature, which has devoted its attention to how firms can profit from their existing technologies (Teece 1986, James et al. 2013). This literature is rather ex post. In this context, Teece (1986) has placed a lot of emphasis on the importance of establishing a dominant design, which is a technological solution of which some features become quasi-standardized, forcing all other alternatives to adopt this standard in order to retain considerable shares of the market (Abernathy and Utterback, 1978, Utterback 1994). While Teece (1986) has established this as a condition, he does not discuss what management has to do to meet it. Our paper offers some insights here. In particular, if network externalities exist, firms should usually seek to realize first mover advantages (Schilling 2002, Srinivasan et al. 2006). In this respect, increasing market reach can be an important cornerstone in the commercialization strategy, not only because it allows the fixed costs of technology development to be spread, but also because it increases the likelihood of establishing a dominant design. Furthermore, Teece (1986) argues that the appropriability regime is important. A point could be made that greater patent breadth is indicative of a firm possessing not only a closed set of core technologies but also many bordering technologies. Such collections of patents' portfolios can create powerful protection walls, often called patent thickets (Shapiro, 2001), because many complementary technologies are under the control of one firm. Therefore, patent breadth might not only reduce technological or market risks, it could also reduce the risk of not appropriating the returns of a technology. In that respect, our results are in line with Teece's classical model of the factors that determine whether a firm profits from its technologies.

This discussion also leads us to a limitation of our theorizing. Although we analyzed the role of technological breadth as a risk reduction strategy, we did not analyze its potential costs. The latter may result from the possibility that diverse knowledge bases are quite difficult to integrate and may prevent spillovers and cross-learning (Helfat and Raubitschek, 2000, Grimpe and Kaiser, 2010). This suggests that diversification cannot increase without bounds, implying the existence of a trade-off between diversity as a hedge against risk and learning potentials. It thus seems reasonable to extend our theory to consider simultaneously the role of diversification in risk reduction and as a determinant in cross-learning between technologies.

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Annex

Table A-1: Size distribution of the companies in the sample (in terms of employees)

Number of employees	**Obs.**	**%**	**Firms**	**%**
0-9,999	711	25,54	112	30,77
10,000-49,999	1297	46,59	211	57,97
50,000-99,999	460	16,52	98	26,92
100,000 and more	316	11,35	59	16,21
Total	**2784**	**100**	**480**	**131,87**

Note: The number of employees was grouped for the purpose of this table but is applied as a continuous variable in all other analyses. The total percentage of firms exceeds 100% since our dataset is in the form of a company-level panel. Thus, a firm might be assigned to more than one category if its number of employees exceeds the given categories in one or more years. The overall N for companies with information on the number of employees is 364.

Table A-2: Country-specific distribution of the companies in the sample

Country	**Obs.**	**%**	**Firms**	**%**
Belgium	16	0,56	2	0,54
Brazil	8	0,28	1	0,27
Canada	45	1,58	6	1,63
Denmark	32	1,12	4	1,09
Finland	32	1,12	4	1,09
France	159	5,57	22	5,99
Germany	145	5,08	19	5,18
Ireland	8	0,28	1	0,27
Israel	14	0,49	2	0,54
Italy	32	1,12	4	1,09
Japan	828	29,01	105	28,61
The Netherlands	55	1,93	7	1,91
Norway	8	0,28	1	0,27
South Korea	8	0,28	1	0,27
Spain	8	0,28	1	0,27
Sweden	80	2,8	10	2,72
Switzerland	95	3,33	12	3,27
Taiwan	16	0,56	2	0,54
UK	150	5,26	20	5,45
USA	1115	39,07	143	38,96
Total	**2854**	**100**	**367**	**100**