Vertical Relationships, Competition, Knowledge Search and Innovation

Empirical Evidence for German Enterprises

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Dipl.-Vw. Christian Köhler

Erstgutachter: Prof. Dr. Kornelius Kraft, Technische Universität Dortmund
Zweitgutachter: Prof. Dr. Dirk Czarnitzki, KU Leuven
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Mannheim, 03. 02. 2014 *Christian Köhler*

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Abbreviations

CIS	Community Innovation Survey
CSS	Cost Structure Survey
GDP	Gross domestic product
GDR	German Democratic Republic
LR	Likelihood ratio
Max	Maximum
Min	Minimum
MIP	Mannheim Innovation Panel
NACE	Nomenclature of economic activities (Nomenclature statistique des activités économiques dans la Communauté européenne)
OECD	Organization for Economic Cooperation and Development
PCM	Price cost margin
PE	Profit elasticity
R&D	Research and development
SD	Standard deviation
TFP	Total factor productivity
US	United States
UK	United Kingdom
ZEW	Centre for European Economic Research (Zentrum für Europäische Wirtschaftsforschung)

1 Introduction

In June 2010 the European Council approved the Europe 2020 strategy which defines the growth strategy of the European Union (EU) for a 10-year period. Europe 2020 succeeds the Lisbon strategy pursued from 2000 to 2010. One important constant in both strategies is the aim of boosting research and development (R&D) activities in order to foster growth of both productivity and jobs thereby assuring increased international competitiveness. The evaluation of the Lisbon strategy shows however, that one of the main goals, namely the goal to spend 3% of the gross domestic product (GDP) for R&D, is clearly missed. In fact during the period from 2000 to 2010 the EU average remained almost constant, moving from 1.85% in 2000 to 1.9% in 2010 (European Commission, 2010a). On EU level, the evaluation report also identifies a "persistent inability to get innovation to the market and turn new ideas into productivity gains" (p. 13). Moreover, the report shows that compared to other countries like the United States (US) or Japan, the gap in R&D intensity (R&D expenditure expressed as share of GDP) is still not closed with the difference being mainly a result of lower levels of private R&D investment.

As a result, Europe 2020 contains many goals that were already included in the Lisbon strategy, among which is also the 3% goal as a means to develop an economy based on knowledge and innovation. The Commission points out clearly that in order to deliver the objectives of Europe 2020 it is vital to enhance key instruments such as the single market. Therefore they are willing to make use of specific competition policy which is supposed to assure that well-functioning markets support competition thereby providing incentives for innovation and growth. From an economist's point of view, the relationship between competition and innovation is not so clear though. In the relevant literature there is a long lasting discussion about how innovation incentives are shaped by competition in a product market. Depending on the assumptions about the type of innovation (e.g. cost-reducing vs. demand enhancing, step-by-step vs. non-step-by-step), the type of market structure before and after the innovation, the strength of patent protection or the dynamics of the innovation process, it is possible to establish negative, positive, u-shaped or inverted u-shaped relations between product market competition and innovation (Gilbert 2006; Vives, 2008; Schmutzler 2009, 2010). Traditionally, economic theory provides a rationale for a negative relationship between competition and innovation incentives which builds on three main arguments. First, fierce competition leads to a reduction of profits and subsequently diminishes internal funding opportunities for innovation projects. Second; intense competition decreases the rents accruing from innovation and third, it increases the uncertainty about competitors' reactions on own innovation activities. As a result firms with ex ante market power have a higher incentive to innovate which is referred to as the Schumpeterian effect or Schumpeter hypothesis II (see, e. g., Schumpeter, 1942; Dasgupta and Stiglitz, 1980). Contrastingly, competition might encourage innovation, as it forces incumbents to innovate in order to keep their position ahead of established competitors or to avoid market entry of new competitors (Arrow, 1962). Recent studies link the effect of competition on innovation incentives also to a firms' technological distance. That is, an increase of competition may have different effects on firms which apply the most efficient technologies compared to firms which are technologically lagging behind (Aghion, 2005; Acemoglu et al., 2006).

To make things even more complex, there are not only effects of horizontal competition that have to be taken into account when examining the innovation incentives of a firm but also effects of competition from downstream markets which are transmitted to vertically linked markets via the relationship between suppliers and their buyers. Suppliers for instance, are increasingly confronted with larger buyers who possess buyer power. Buyer power refers to a situation with a downstream firm having monopsonistic power or bargaining power vis-à-vis its suppliers'. Monopsonistic power is characterised by a downstream market with just one active firm which is connected to an upstream market under perfect competition with numerous price taking firms (see e. g. Mas-Colell et al., 1995). The main argument of this approach is that monopsonistic firms strategically reduce demand in order to maximise profits. However, this may not apply to most vertical relationships. Hence, the bargaining approach emerged in order to reflect the very common habit to negotiate over prices and quantities in intermediate markets.[1] This approach assumes that supplier and buyer negotiate bilaterally over prices and quantities of the respective good or service to be traded. Given that contracting between the supplier and the buyer leads to joint profit, the split of the profit then depends on the bargaining power of each contracting party. The strength of bargaining power is determined by the profits to be realised when the contract is made with an alternative supplier or buyer. The higher such disagreement or outside-option payoffs in relation to the

[1] Björnerstedt and Stennek (2007) cite an estimation of *The Economist* that about 80 to 90% of all intermediate goods are traded through extended term contracts.

counterparts payoffs the stronger the bargaining position of the respective contractor. According to this approach, buyer power results from the fact that more valuable outside options are at the disposal of the buyer thereby allowing the buyer to extract a larger share of joint profits (Inderst and Valletti, 2007; Dobson and Inderst, 2008). As a result the distribution of bargaining power between contractors will influence incentives to carry out investments such as R&D because it has an effect on the appropriability of the rents accruing from these investments. At the same time, R&D activities may be a way for suppliers to increase their bargaining power as R&D is usually leading to lower production cost or improved product quality. This will result in a devaluation of the buyer's outside options by decreasing the buyer's profits from a contract with an alternative supplier.

The European growth strategy Europe 2020 contains also instruments by which the delivery of the strategy's objectives is backed up. One of those instruments is the flagship initiative "Innovation Union" which is intended to enhance framework conditions for innovation and R&D on one hand and the accessibility of financial means for research and innovation on the other hand. The implementation of this flagship initiative is supposed to ensure “that innovative ideas can be turned into products and services that create growth and jobs” (European Commission, 2010b; p. 12). To this end, the initiative encompasses among others actions on both EU and national level to support links between education (universities), business and research and innovation. The strengthening of these links is important as firms can benefit from connecting their own innovation activities to external know-how since doing so enables them to absorb innovation impulses from other players in the innovation system. The increasing adoption of such cooperative behaviour is in sharp contrast to research and development carried out merely within the bounds of an enterprise. Literature reflects this change in enterprises' innovation strategy in the concept of “open innovation” (Chesbrough, 2003).

The implementation of open innovation activities is on one hand sparked by changes in enterprises' economic environment: product lifecycles become shorter, technological opportunities emerge beyond enterprises' traditional fields of expertise while at the same time competition intensifies (e. g. Calantone et al., 1997; Chatterji, 1996; Kleinschmidt and Cooper, 1988; Ojah and Monplaisir, 2003). On the other hand the availability of external knowledge resources increases. Highly qualified researchers and engineers are more and more mobile, venture capitalists alleviate the commercialisation of new inventions and suppliers increasingly specialise thereby providing highly specific services, materials and equipment (Chesbrough, 2003). Several studies have identified positive enterprise performance effects of incorporating external knowledge into internal knowledge stocks (e.g. Gemünden et al., 1992; Laursen and Salter, 2006; Love and Roper, 2004). A crucial element in the open innovation activities of firms is a firm's search for external knowledge. A firm's external knowledge search encompasses an "organization's problem-solving activities that involve the creation and recombination of technological ideas" (Katila and Ahuja, 2002, p. 1184). Consequently, investments in problem-solving activities should result in favorable combinations and linkages of users, suppliers and other relevant actors in the innovation system. Laursen and Salter (2006) discuss the concepts of breadth and depth as important factors in a firm's search. Leiponen and Helfat (2011) complement this view by extending the concept of breadth to innovation objectives. They find that the breadth of knowledge sources and of innovation objectives positively influences innovation success at the firm level. Although a broader set of external sources and innovation objectives reduces the risk of unexpected developments, it has to be taken into account that a firm is constrained in terms of the capacity to absorb external knowledge (Cohen and Levinthal, 1989, 1990).

This thesis is related to the instruments applied in Europe 2020 in order to reach the goals defined in the growth strategy: innovation incentives arising from competition and vertical relationships as well as the strengthening of links between actors in the innovation system. The contribution of this work is to provide empirical evidence on the effects that can be expected to occur when these instruments are applied successfully.

The first part of this thesis deals with the effects of bargaining in vertical relationships on suppliers' R&D profitability and innovation incentives. So far, existing studies neglect vertical relations and possible effects emanating from them. Section 2.1 studies how a supplier's R&D profitability is affected by the strength of his bargaining position. To this end, the main determinants of suppliers' bargaining power are identified, namely the market position and the concentration in the buyer portfolio. While the former will strengthen suppliers' bargaining power, the latter has an adverse effect. Departing from results of theoretical and empirical literature concerning vertical relations between suppliers and buyers, hypotheses are derived which are subsequently empirically tested.

The effects of buyer power, i. e. a stronger bargaining position of the buyer compared to the supplier, on suppliers' innovation incentives are considered in section 2.2. So far, this relationship has been discussed largely on theoretical ground while empirical evidence is rare. In addition, existing studies often lack an objective measure for buyer power on firm level but rather use either aggregated industry measures or firms' subjective assessment whether they are confronted with powerful buyers. Furthermore, analyses of the relationship between buyer power and suppliers' incentives to innovate are mostly focused on particular industries which are perceived to be heavily affected by concentration processes among buyers. Also, effects due to high competition or intense R&D in buyer industries are neglected.

In contrast to existing studies, section 2.2 applies objective measures that allow for different degrees of buyer power. Competition and technology intensity of buyer industries are taken into account and a first attempt to explore joint effects between buyer power and downstream industry environment is undertaken. Finally, the effects of buyer power on the suppliers' innovation incentives are disentangled into the effect on the decision to start innovation activities and the effect on the amount of resources spent on innovation.

Chapter 3 is dedicated to the effects of horizontal competition on firms' innovation incentives. One of the difficulties in such a study is the measurement of competition. We compare a recently proposed competition measure on industry level – the profit elasticity (Boone; 2008) with a traditional firm level competition measure, namely the price cost margin. In addition, recent studies hint in the direction that innovation incentives are not only affected by competition effects but also by a firm's technological distance as well as the technological spread between firms within an industry (Aghion et al., 2005; Acemoglu et al., 2006). Therefore we also test how a firm's technological distance and the technological spread within an industry may interact with competition effects.

Chapter 4 investigates the links between actors in the innovation system and how they can be successfully exploited by enterprises. We argue that firms' knowledge search targets particular knowledge sources (e.g. customers, universities, suppliers) depending on both the type of innovation and the sector they are active in. To this end, we integrate the role of knowledge search into particular sectoral patterns of innovation which are derived from a novel typology of sectoral patterns of innovation (Castellacci, 2008; 2010) and distinguish between imitation and new-to-market innovation output.

A summary of the chapters' findings and subsequent conclusions are presented in chapter 5.

2 Bargaining in vertical relationships

This chapter presents work on issues of bargaining in vertical relationships and deals with effects on suppliers' R&D profitability as well as innovation incentives in particular.

Section 2.1 links bargaining in vertical relationships to suppliers' R&D profitability. Section 2.2 is a joint work with Christian Rammer and investigates the effects of buyer power on a supplier's innovation incentives taking into account the market environment of the buyer.

2.1 Bargaining in vertical relationships and suppliers' R&D profitability

2.1.1 Introduction

R&D is considered to be one of the most important drivers of firm productivity and consequently of economic growth and welfare. Thus, considerable amounts of public spending are directed towards programmes promoting R&D investment on firm level. It is by no means clear however, whether R&D investments are profitable since the costs are high, the outcome is uncertain, the risk of failure is considerable and profits accruing from these investments typically have a significant time lag compared to other types of investment.

It is well known that the profitability of R&D strongly depends on the market environment of the firm. Traditional industrial organization literature emphasizes the importance of market concentration and entry barriers for firm profitability (for an overview see Schmalensee, 1989) and this has been shown to be important for the profitability of R&D as well (Grabowski and Müller, 1978; Conolly and Hirschey, 1984; Czarnitzki and Kraft, 2010). Another factor that may be important – and which has been neglected in existing studies – is the relative bargaining power that an R&D performing firm possesses in negotiations about prices and quantities with its buyers. Such vertical relationships between suppliers and buyers receive growing attention from economists, especially since it has become accepted that larger buyers may benefit from buyer power. Often, the emergence of buyer power is attributed to concentration processes among buyer firms (see e. g. Chipty and Snyder, 1999, Inderst and Wey, 2007). Such processes however are not sufficient for generating buyer power. In Germany for instance, one can observe that for a third of all firms the three largest customers account for 50-100% of their sales (Aschhoff et al., 2007). Such a concentrated customer structure may lead to buyer power as well, notably if the supplier is small and the buyer large. The execution of buyer power is seen as predominantly negative, since it lowers the profit of the suppliers, thereby lowering their investment incentives (OECD, 1998; European Commission, 1999a).

As R&D translates into new products or lower costs of production not only on the supply side but also on the buyer side, bargaining over the distribution of the accruing profits along the supply chain between supplier and buyer may occur and affect the profitability of suppliers' R&D investments considerably. On one hand, if the buyer has the stronger bargaining position, i. e. he has buyer power, it is possible that large parts of the gains from a supplier's R&D activity will be appropriated by the buyer. On the other hand, if the supplier has the stronger bargaining position it is possible that he can extract significant shares of the buyer's profit. To the best of my knowledge, there is no study dedicated to the analysis of R&D profitability however, taking account of these opportunities. Hence, the main contribution of this paper is the integration of bargaining power in vertical relationships into the analysis of a suppliers' R&D profitability.

Section 2.1 will deal with two major research questions. First, which factors determine the bargaining position of a supplier in a vertical relationship and how do these factors affect a supplier's profitability? Second, how does the bargaining position affect the profitability of supplier's R&D investments? I will explore these questions empirically using a dataset of 472 German manufacturing firms which contains information on the relationship to their buyers.

The next section presents existing empirical literature on the profitability of R&D. Section 2.1.3 reviews theoretical and empirical findings on the impact of bargaining in vertical relationships and derives empirically testable hypotheses how bargaining affects suppliers' R&D profitability. The empirical approach is described in section 2.1.4, while results are presented in section 2.1.5. Concluding remarks are given in section 2.1.6.

2.1.2 Literature overview

Empirical studies dedicated to the analysis of the relationship between R&D or innovation activities and firm profitability provide mixed results on the relationship between R&D, innovation and firm profitability. Most of these studies include to some extent measures capturing the horizontal market structure which is in line with traditional industrial organization literature that emphasizes the importance of market concentration and entry barriers for firm profitability (for an overview see Schmalensee, 1989). Vertical relations and the possible consequences on suppliers' bargaining power are not considered however.

Among the studies using US data, Mansfield et al. (1977) assess the private and social returns of seventeen industrial innovations. They find pre-tax private returns ranging from negative values to 214% with a median of 25%. In 30% of the cases though, the private returns were so low that no firm in hindsight would have invested in that project. Nevertheless the social returns exceeded the private ones considerably, ranging from negative values to 307% with a median of 56%. Grabowski and Müller (1978) find a positive impact of R&D on adjusted profit rates of US firms. They also consider market concentration in order to test the hypothesis that R&D in combination with high concentration may act as a catalyst of competition. They suggest that while there is a tendency of cartelistic behaviour in concentrated industries, R&D delivers an incentive to deviate from collusive agreements because it is difficult to coordinate between the cartelists. Hence, R&D can induce rivalry in otherwise cartelistic markets. This is supported by the empirical results. More evidence for this hypothesis is provided by Conolly and Hirschey (1984) who estimate a simultaneous equation model with R&D intensity, advertising intensity, firm profitability and the concentration ratio as endogenous variables. With respect to the impact of R&D on firm profitability they find a positive effect of R&D. Jaffe (1986) estimates a three-equation model using a dataset of 432 US firms with patents, profit measured as the operating income before depreciation and market value as dependent variables. The results show that the average gross rate of return of R&D is 27%. The concentration rate measured as the four firm concentration ratio is negatively affecting firm profits.

Evidence for Europe is provided by several papers employing data from the Community Innovation Survey (CIS). Recent papers of Czarnitzki and Kraft (2010, 2012) use a sample of German manufacturing firms and explore the effect of patent stocks, R&D

intensity and spillovers on firm profitability. Czarnitzki and Kraft (2010) find a positive effect of patent stock but no effect of R&D intensity. With regards to the competition variables they find that concentration is positively affecting firm profitability while market share is insignificant. In addition they estimate a negative coefficient for the interaction between R&D and concentration thereby supporting the hypothesis of Grabowski and Müller (1974). In contrast, Czarnitzki and Kraft (2012) test for a non-linear relationship between firm profitability and R&D. They find evidence for an up-ward sloping curve with decreasing marginal returns. What is more, an effect of concen-tration on firm profitability cannot be detected. Mata and Woerter (2013) explore the impact of external and internal R&D on price-cost margins for Swiss firms. They do not consider any market structure at all and find firms with both external and internal R&D activities to be more profitable than firms with merely internal R&D. Rexhäuser and Rammer (2014) also use a dataset of German firms but find no effect for the magnitude of the patent stock and the introduction of market novelties or cost saving innovations on firm profitability. In line with Czarnitzki and Kraft (2012) they do not find an effect of horizontal concentration. Their results show however a strong negative effect on profitability for a competition dummy variable which is a composite competition index taking unit value if the firm indicates that at least one of the following characterizations apply to their main product market: entry of new competitors, products and services are quickly outdated, the firm’s products can be easily substituted by competitors’ products, strong competition from abroad and uncertainty in demand or competitors actions.

Geroski et al. (1993) use a panel of 721 British firms observed during the period 1972 to 1983. They do not consider R&D but innovative outputs and assess the impact of the latter on firm profitability. They find a positive effect of an additional innovation on firm profitability. Moreover, the results provide evidence that differences in profitability between innovators and non-innovators are persistent with innovators exhibiting a high-er profitability. In addition, Geroski et al. (1993) are the first to hint at the importance of vertical relationships when assessing the profitability of a firm in combination with its innovative efforts. They note that innovations in their dataset “have had a far greater impact on users' productivity growth than on producers' productivity (e.g., Geroski, 1991), and there is no reason not to think that this might also be true with profitability” (p. 208).

This statement reflects exactly why the distribution of bargaining power in vertical rela-tionships may be an important factor in determining a supplier’s profitability. Given that a supplier’s innovative product or process does have a greater impact on downstream profitability, he may extract a share of the downstream profit through bargaining. How much of the downstream profit can be extracted depends on the strength of the supplier’s bargaining position relative to the bargaining position of the buyer. Conversely, if the buyer does have a stronger bargaining position compared to the supplier, the former can reduce the profits of the latter by extracting a large part of the upstream profit.

To the best of my knowledge, there is no existing study however, taking account of these opportunities. Hence, the main contribution of this paper is taking account of bargaining power in vertical relationships when analysing the profitability of suppliers’ R&D.

2.1.3 Theoretical framework

In this section I study how the profitability of suppliers’ R&D investments is affected by bargaining power. To this end, theoretical and empirical findings are reviewed. Subsequently hypotheses are derived that can be tested empirically.

First, I will consider how a supplier’s profitability is affected by bargaining power. Major determinants of bargaining power in vertical relations are firm size and market concentration. Theoretical literature on vertical interactions frequently predicts a negative effect of buyer concentration on supplier profitability due to buyer power (e. g. Dobson and Waterson, 1997; Inderst and Wey, 2007, Smith and Thanassoulis, 2012). Usually this finding is derived from Nash bargaining models applying different assumptions on efficiency of the outcome, upstream and downstream market structure, uncertainty over output quantities as well as a supplier’s cost function. In most of these models it is assumed that there is one supplier negotiating simultaneously with numerous buyers over the split of a joint profit v. The joint profit v is the sum of the upstream and the downstream profits generated by the contract between supplier and buyer, which I will refer to as “incremental profits” in the following. In a given negotiation the outcome of all other negotiations is taken as given, hence the negotiations with a certain buyer are over the last units of the intermediary product.

Assuming inefficient Nash bargaining, i. e. bargaining over linear unit prices, buyers can reduce upstream profits if downstream concentration increases (Dobson and Waterson, 1997). This is due to the fact, that the outside option of the supplier, i. e. the prices and quantities he can sell to all other downstream firms in case the negotiations with a certain buyer fail, is devaluated since there are less alternative buyers available. If in addition downstream firms are very competitive (i.e. their products are perceived to be close substitutes) and behave in a Bertrand manner, supplier's profits are driven down even further as the incremental downstream profit is close to zero and consequently the joint profit v decreases.

In the case of efficient Nash bargaining, i. e. contractors maximize the joint profit and can settle on non-linear prices, similar results occur. Given the supplier can be certain over the final upstream quantity demanded, input prices are a function of average costs of supplying the buyer. Consequently a large order in combination with increasing marginal costs of the supplier implies lower input prices (Chipty and Snyder, 1999; Inderst and Wey, 2007). To derive this result it is necessary that downstream firms are considered as monopolists on symmetric but separate markets with marginal costs of transforming the intermediate product of zero. In this case the optimal quantity provided by the downstream firm is independent of the market size and hence the downstream price is constant over all downstream markets. It follows then that only the incremental upstream profit is relevant for the emergence of buyer power and ultimately lower supplier profitability. Relaxing the assumption that downstream prices have to be constant across markets, Björnerstedt and Stennek (2007) derive buyer discounts also for the case of multiple upstream and multiple downstream firms. They argue that the relation of a buyer's marginal revenue and a supplier's marginal cost determines whether there is a quantity discount or a quantity premium for buyers. If marginal cost of the supplier is steeper than marginal revenue of the buyer, an increase in quantity for the buyer reduces incremental cost of supply more than it increases downstream revenues, ultimately leading to a quantity discount for the buyer.

In the presence of uncertainty over upstream final output, a supplier's profitability decreases if there are large buyers, i. e. buyers who account for large share of the supplier's sales, and decreasing marginal costs of supply (Smith and Thanassoulis, 2012). This is due to the fact that a supplier now attaches a probability of losing a contract to volumes negotiated with a buyer. The average costs of supplying the buyer are now not calculated over the final units but over all possible output realizations. Hence larger buyers imply larger expected output, lower expected marginal cost and thus lower input prices.

In line with the presented results from theoretical literature one can argue that increased buyer concentration is likely to have a negative effect on supplier's profitability. Accordingly, the first hypothesis reads:

Hypothesis 1: *The profit of the supplier is decreasing the more concentrated the buyer portfolio.*

Next I will show how a supplier's bargaining position is affected by his market position and which effect this will have in turn on his profits. A supplier's market position is defined on one hand by the market structure in the horizontal market and on the other hand by the substitutability of the supplied product. A monopoly in the supply market does not allow for an outside option of the buyer which in turn should result in a more powerful bargaining position of the supplier in comparison to a supplier with a high number of competitors. Such a beneficial market position is for instance obtainable by product differentiation thereby making the own product less substitutable.

Empirical studies dedicated to the analysis of manufacturer-retailer relationships in the food sector hint in the direction, that lower substitutability increases supplier margins. This is shown for yoghurt and peanut butter in the US (Sudhir, 2001), antibiotics in the US (Ellison and Snyder, 2010) and coffee in Chile (Noton and Elberg, 2012). If downstream product markets are very competitive because the products are easy to substitute, there is evidence for the existence of buyer power. For instance, for a yoghurt market in a particular region of the US with a considerable market share of private labels, there is support for the existence of two-part tariffs with zero wholesale margins (Villas-Boas, 2007).[2] A two-part tariff is characterized by the feature, that the manufacturer sets the wholesale price equal to marginal cost, so the retailer can claim all the profit for the product. The manufacturer is able to extract part of this wholesale profit in the form of a fixed fee the retailer has to pay. If wholesale profits are zero however, this implies that all the profit remains with the retailer. Hence suppliers' profitability is reduced.

Another way to achieve a monopoly position is patent protection. For antibiotics without patent protection, i.e. if competition with generic products is prevailed, large buyers (chain drugstores) receive discounts when compared to smaller buyers (Ellison and Snyder, 2010). Again, this implies a lower profitability on the supply side if substituta-

[2] Two-part tariffs are considered to be the optimal contract whenever there is downstream market power. This holds for certain demand or asymmetric information (Tirole, 1988) and uncertain demand (Rey and Tirole, 1986). If there are multiple retailers and multiple manufacturers however, two-part tariffs are no longer the optimal contract (Schmalensee, 1981).

bility is high. Against the background of these empirical results, it is obvious that suppliers' profitability positively depends on the strength of their market position. Consequently, the second hypothesis is stated as follows:

Hypothesis 2: *The profit of the supplier is increasing in the strength of the market position.*

The theoretical results this section builds on, typically consider negotiations over price and quantity of a good to be traded between supplier and buyer with rational agents. Williamson (1975) however, does acknowledge that agents may be boundedly rational, i. e. they have incomplete information about market opportunities and future occurences for instance (Alchian and Woodward, 1988) and are prone to failure. What is more, agents can behave opportunistic in a way, that they disclose information selectively and / or distortedly or simply give false promises regarding future conduct (Williamson, 1975). Such behaviour gives rise to transaction costs which may have an adverse impact on vertical relationships.[3] In the context of R&D, transaction costs may be substantial if R&D is sourced out or performed within an alliance (Aghion and Tirole, 1994). Under such circumstances, suppliers of R&D services can have several motives to behave opportunistically: "increasing the profits by reducing the efforts, preparation of own competitive activities and selling non-specific parts of the generated knowledge to a competitor (Kloyer and Scholderer, 2012; p. 347)". The buyer may also be tempted to behave opportunistically. That is, after the R&D supplier carried out necessary investments to fulfil contracted obligations, the buyer may enforce ex-post negotiations leading to conditions which reduce the supplier's profit margins or even lead to losses. Such behaviour is known as hold-up (Klein et al., 1978).

This paper considers internal R&D investments of suppliers, i. e. investments that aim at the development or the significant improvement of production technologies or products to own benefit. Hence, problems of information asymmetries between supplier and buyer and subsequent opportunities for moral hazard or hidden actions may not be as severe as in contractual R&D relationships. If there are opportunities for one party to behave opportunistically however, it should be the party in possession of the stronger bargaining position. This implies that even in the presence of opportunistic behaviour, suppli-

[3] Transaction cost economics have been applied not only to vertical relationships but to a wide range of economic matters, e. g. "transfer pricing, corporate finance, marketing, the organization of work, long-term commercial contracting, franchising, regulation, the multinational corporation, company towns, and other contractual relationships, both formal and informal" (Shelanski and Klein, 1995; p. 336).

ers' profitability should be positively (negatively) affected by a stronger (weaker) bargaining position.

Regardless of bargaining power, it has been shown frequently in empirical work that R&D activities are a main driver of firm productivity (e. g. Griliches, 1994; Crepon et al., 1998; Griffith et al., 2006a; Peters, 2008). This is due to the fact that R&D translates into new products and/or new production processes, thereby offering the opportunity to charge higher prices (for new products) or to benefit from lower cost of production for a given output. Of course, among firms there may be different strategies of performing R&D. That is, some firms carry out R&D incrementally, i. e. they alter existing technology; while some others concentrate on developing new-to-the-market products and/or technologies. No matter which strategy is applied, R&D will at some point result in an innovation which gives a firm a competitive advantage.

In addition to the positive effects of R&D on suppliers' profitability, there are also positive effects to be expected on the profitability of buyers. Using industry data from the UK, Geroski (1991) shows that the biggest impact on productivity growth came from innovations used rather than innovations produced. Scherer (1982a) distinguishes the allocation of R&D expenditure by industry of use and industry of origin and explores the relationship to productivity growth in the US. In line with the results of Geroski (1991) he finds the R&D expenditure allocated to industry of use to have a larger effect on productivity growth. Hence, it seems plausible to assume that supplier's R&D can enlarge the joint profit which is to be split between supplier and buyer by bargaining. On one hand, if bargaining power of a supplier carrying out R&D activities is weak it is not possible to appropriate a large share of the joint profit (Farber, 1981; Lunn and Martin, 1986; Peters, 2000). On the other hand, if bargaining power of a supplier is high, he may be able to extract parts of the downstream profit that accrue due to an innovative product, for instance. The corresponding hypotheses for the effect of bargaining power in vertical relationships on the profitability of suppliers' R&D activities read:

Hypothesis 3: *The profitability of R&D investment increases with the strength of a supplier's market position.*

Hypothesis 4: *The profitability of R&D investment decreases with the concentration of a supplier's buyer portfolio.*

2.1.4 Empirical study

2.1.4.1 Data

In order to test the hypotheses empirically I employ firm level data from the Mannheim Innovation Panel (MIP) which provides information on enterprises from both manufacturing and services located in Germany and employing at least 5 employees. The data is annually collected by the Centre for European Economic Research (ZEW) on behalf of the Federal Ministry of Education and Research. The survey focuses on enterprises' innovative activities but also includes questions on their competitive environment.[4]

The 2011 wave of the MIP provides valuable information on supplier-buyer relationships and enterprises' market environment. Since the question regarding the supplier-buyer relationship is not part of the regular questionnaire, it is not possible to construct a panel dataset. The wave 2011 also contains general information, e. g. the profit over sales, the number of employees or the sales, but also information on the innovation behaviour and R&D spending. In order to have a lag between the dependent profit variable and the explanatory variables the wave 2011 is merged with the wave 2013 since the question regarding the profit is included biannually. I restrict the sample to manufacturing firms because services comprise rather heterogeneous industries. Additionally, R&D does more frequently occur in manufacturing. There are 1,411 firms for which the merge was successful representing Nace 2-digit industries 10-17 and 20-33.[5] To avoid outlier problems I drop all three observations with an R&D intensity of larger than 2, i. e. a firm's R&D expenditures exceed the sales by 100 % leading to an initial sample of 1,408 firms. The further steps of data cleaning are described in the next section.

2.1.4.2 Variables

Dependent variable

The dependent variable is a supplier's profit over sales (*PROFIT*). This variable is available for both years 2012 and 2011 and thus provides an interesting opportunity to check if the impact of R&D investments in 2010 on supplier's profitability does have a time lag as suggested by Ravenscraft and Scherer (1982).[6]

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[4] For a more detailed description of the MIP see Peters (2008) and Peters and Rammer (2013).

[5] The Nace codes refer to the Nace Rev. 2. The breakdown of industries is presented in Table A 1 in Appendix A.

[6] Using US data they find a mean lag of 4 to 6 years.

The profit over sales variable was surveyed as categorical variable. Table 2.1 provides an overview of the different categories. Although provided with a category “don’t know”, some of the participating firms did not answer the question at all.

Table 2.1: Surveyed categories of the return on sales

Return on sales	Class	Return on sales	Class	Return on sales	Class
< -5%	1	[2, 4%)	5	>15%	9
[-5, -2%)	2	[4, 7%)	6	Do not know	10
[-2, 0%)	3	[7, 10%)	7		
[0, 2%)	4	[10, 15%)	8		

From the initial sample of 1,408 firms, 111 answered “don’t know” to the profit in 2011 while 120 firms did so to the profit in 2012. Another 238 firms did not respond at all to the profit in 2011 (2012: 249 firms). Since the profit over sales variable is sensitive information and firms may be reluctant to provide information on it, I follow Czarnitzki and Kraft (2010, 2012) and perform an analysis if there are systematic differences between respondents and non-respondents. The detection of systematic differences would indicate that the estimations presented in next subsection suffer from a selection bias. Therefore I generate two dummy variables: the first takes unit value if the firm did not respond to the question at all while the second indicates if a firm did not respond or checked the “don’t know” category. Then, Probit models are estimated for each year separately, regressing the dummy variables on all explanatory variables presented below. After deleting all observations with missing values in the explanatory variables, I eventually arrive at a sample of 570 observations, of which 472 do report profit over sales in both years 2011 and 2012.[7] I perform Wald-Tests to check if the coefficients are jointly significant. The test statistics take the value 19.79 (2011) and 21.59 (2012) for the model using the first and 16.52 (2011) and 18.08 (2012) for the model using the second dummy variable. All test statistics are distributed with 23 degrees of freedom. The corresponding p-values are 0.60, 0.49, 0.83 and 0.75 respectively, implying that there are no systematic differences between responding and non-responding firms. Obviously, this procedure controls for selection on observables. Given the various control

[7] Missing values in the dependent and explanatory variables would have led to a final sample of 676 observations. I decided however to exclude another 204 firms which indicated to have a market share of less than 0.1 % or a share of sales generated by the largest three customers of less than 1 %. The reasons are explained when describing the variables buyer concentration and market share.

variables which were applied, I conclude however that selection is not a concern in the final sample.

The profit over sales represents the excess return on sales and expresses the profits (sales – labour cost – capital cost – material cost) over sales. Czarnitzki and Kraft (2010, 2012) show that under certain assumptions the return on sales represents the Lerner index.[8] As the return on sales is net of capital costs, there is no need to include an additional explanatory variable controlling for the costs of capital.

Explanatory variables

The goal of this study is to explore the relationship between profitability and R&D investments taking into account the distribution of bargaining power in vertical relationships. Hence, R&D investments are measured by R&D intensity (*RDINT*) of the supply firm in 2010 which is defined as R&D expenditure over sales. It is unclear though if the effect of *RDINT* can be expected to be positive or negative (see subsection 2.1.2). The latter can occur if it is true that R&D performing firms face difficulties to find external capital lenders (see e. g. the survey of Hall and Lerner, 2010 and the references cited therein). As a result, risky and uncertain R&D projects are predominantly financed with internal financial means, implying a reduction of the supplier's profitability.

The bargaining power of the supplier is represented by the supplier's market position and the concentration of his buyer structure. The concentration of the buyer structure (*BUYCON*) is derived from a question regarding the share of sales generated by the largest three buyers in 2010, which could be filled in by respondents directly. Obviously, it would be preferable to have the share of each single buyer in the supplier's sales but the measure still allows testing of hypothesis 1 as a large value of *BUYCON* should indicate also large shares for single buyers.[9] In addition, the questionnaire included a check box which could be ticked if the share of sales with the largest three buyers is below 1 %. I chose to drop all observations with a sales share of the largest three buyers below 1 % as I am interested in intermediate markets and I assume that these firms rather work on final product markets.

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[8] These assumptions are that firms are in the long-run equilibrium and produce with constant returns to scale. Then the returns on sales of a firm represent on average across the product portfolio the Lerner index since average costs equal marginal cost when returns to scale are constant.

[9] Note that the observed share reflects the share of sales generated by three customers. If firms have less than three buyers, the share equals 100 %.

A supplier's profitability should be also affected by the concentration in the downstream market as a high concentration does not allow for easy switching of buyers. Since the dataset contains only limited information about the buyers, I cannot observe the product markets they are active in. This is clearly a limitation of this study. However, downstream concentration should be captured at least partly by industry dummies controlling for differences in suppliers' industry characteristics, if suppliers in a particular industry are affected equally by downstream concentration.

The market position of the supplier which was identified as determining the supplier's bargaining power is captured by several variables. Recall that the market position depends on the switching costs of buyers and reflects market structure and the substitutability of the supplied product. For instance, switching costs should be low if the intermediate good is homogenous and durable and numerous suppliers produce it. In contrast, they should be high if the good is very customer-specific. Hence, the number of a supplier's competitors (*COMP*) is included to control for switching opportunities of buyers. *COMP* is a dummy variable indicating whether the number of competitors is within the range of 1 to 5.[10] The reference category thus is to have no or more than 5 competitors.[11] In order to control for substitutability, I use the assessment of the supplier whether the firm's product is easy to substitute by competitors' products on a 4-point-Likert-scale.[12] I construct a dummy variable (*SUBSTIT*) taking unit value if the firm agrees or fully agrees to the above statement.

The main variable reflecting a supplier's market position is the supplier's market share in the main product market (*MSHARE*). Firms were asked directly for their market share with the most important product in 2010 and could check a box, if it was below 0.1 %. The share of responding firms in the initial sample with a market share below 0.1 % was about 30 % which seems remarkably high. Further inspection showed that some quite large firms were within this group.[13] This is surprising as larger firms should report larger market shares. As the questionnaire did not provide an option to answer "don't

[10] The corresponding question asks for the number of competitors on the main product market and provided the categories "None", "1 to 5", "6 to 10", "11 to 15", "16 to 50" and "more than 50" to answer.

[11] I also experimented with the inclusion of a dummy variable indicating if the supplier is a monopolist. The estimated coefficient of the variable was however highly insignificant while all other results were unchanged. Hence, I refrain from using this variable.

[12] The respondent could assess the statement with "do not agree", "somewhat disagree", "somewhat agree" and "fully agree".

[13] About 10 % of these firms reported to have more than 100 employees.

know" for the market share, it seems reasonable that a significant share of firms ticked the threshold box because they did not know how large their market share is. Hence, as a measure of precaution and since I do not have the opportunity to cross check the information with other data, I excluded all firms reporting market share below 0.1 %.

Apart from the fact that market share is a more objective measure, it is also more detailed compared to *SUBSTIT* and should in addition capture factors like buyer loyalty or the strength of a brand which have impact on the substitutability of a product. However, the choice of the market share as measure of a supplier's bargaining power deserves further discussion. The underlying assumption is that if a supplier's market share is large, then – from the perspective of a buyer – there are fewer alternative suppliers to turn to in case the negotiations with the supplier fail. Hence, the supplier has higher bargaining power compared to a supplier with low market shares. What is more, the market share can also be interpreted as a sign of higher efficiency. This interpretation goes back to the "Chicago School" (see e. g. Demsetz, 1973 or Peltzman, 1977) and builds on the assumption that there are productivity differences between firms within a market. Competition between these firms leads to a reallocation of market shares from inefficient to efficient firms. Hence productive firms grow, increase their market share and are more profitable while less productive firms shrink and eventually exit the market. That is, the efficiency argument would imply a stronger bargaining position for a supplier with a high market share since the outside option for a buyer would be to turn to a supplier operating on a higher cost curve.

Using the market share as a measure of a supplier's bargaining power comes with a caveat though. According to the simple Cournot model with homogenous goods, the market share determines the price-cost margin of a firm, i. e. the higher the market share, the higher a firm's profitability (see e. g. Belleflamme and Peitz, 2010). This would imply a relationship between market share and firm profitability which is detached from bargaining. However, the model neglects at the same time both vertical interaction and the existence of transaction costs. As I have shown in the previous section transaction costs may play an important part in vertical relationships. Also an overwhelming part of the transactions on intermediate markets are sealed by bargaining.[14] Hence, the interpretation of the market share as a determinant of bargaining power seems to be reasonable.

[14] Björnerstedt and Stennek (2007) cite an estimation of *The Economist* that about 80 to 90% of all intermediate goods are traded through extended term contracts and that spot markets play a fairly minor role.

Even though I consider *BUYCON* and *MSHARE* to be the main variables of interest in measuring suppliers' bargaining power, there are other factors affecting the contractors bargaining position and thereby influencing a supplier's profit. The elasticity in demand may be an important factor as a supplier could make up the loss of a buyer or concessions in prices with increasing the prices for remaining buyers.[15] The leeway for such price increases should be the larger, the less price elastic demand. To control for that, three dummy variables are included in the estimation equation, indicating to what extent the supplier agrees with the statement, that an increase in prices leads to an immediate loss of customers on a 4-point-Likert-scale. If they strongly agree, I assume the price elasticity of demand to be high (*ELAST_H*), while it is assumed to be medium, if the supplier somewhat agrees (*ELAST_M*). The price elasticity of demand is assumed to be low if the supplier somewhat disagrees (*ELAST_L*). Consequently, the reference category consists of firms which strongly disagree with the above statement and therefore face a relatively inelastic demand. Finally, a high degree of product diversity offers more outside options to the supplier compared to a single-product-supplier. In the questionnaire firms where asked for the share of sales with their most important product. In order to control for a firm's product diversity, I include a variable (*DIVERS*) that is defined as 100 minus the share of sales with the most important product. *DIVERS* thus reflects the share of sales a firm generates with others than its most important product.

Further firm specific characteristics that may affect a supplier's profitability are also considered. Firms involved in international trade are likely to be more competitive as they are able to enter foreign markets. Moreover, after entering they serve presumably larger markets. Thus a variable indicating the export intensity (*EXPORT*) is included which is defined as the share of exports in sales. To capture size effects the firm size (*SIZE*) measured as the log of the number of employees in full time equivalents is included. Another dummy variable is included in order to control if the firm is part of a multinational enterprise group (*FOREIGN*). Further control variables are whether the firm is located in Eastern Germany (*EAST*) and 10 industry dummies (*IND*) with the furniture/sport/toys industry as reference.

[15] The observation of low prices for large or powerful buyers while the remaining buyers' prices increase, is described as “waterbed effect” (see Inderst and Valletti, 2008, Smith and Thanassoulis, 2012).

2.1.4.3 Estimation strategy[16]

Given the theoretical framework and the variables identified in the previous section, the empirical strategy is formulated according to equation (2.5).

$$PROFIT_{i,t+2} = \beta_0 + \beta_1 RDINT_{it} + \beta_2 MSHARE_{it} + \beta_3 BUYCON_{it} + \delta X + \varepsilon_i \qquad (2.5)$$

Vector X includes all variables which were identified to affect the bargaining power of the supplier and thus profitability, i. e. the substitutability of the supplier's product (*SUBSTIT*), the price elasticity of the demand (*ELAST_H*, *ELAST_M*, *ELAST_L*), the number of competitors (*COMP*) and the supplier's degree of diversification (*DIVERS*). In addition, vector X contains further variables capturing firm characteristics, i. e. *EXPORT*, *SIZE*, *FOREIGN*, *EAST* and the industry dummies.

Since the dependent variable is categorical, an ordered Probit model is estimated to obtain the influence of R&D investments and the supplier's bargaining power on profitability. Hence, equation (2.5) defines our latent model of the unobserved dependent variable $PROFIT_i^*$. The observed profit over sales relationship is defined by:

$$PROFIT_i = \begin{cases} 1 \text{ if } PROFIT_i^* \leq \mu_1 \\ 2 \text{ if } \mu_1 < PROFIT_i^* \leq \mu_2 \\ \vdots \\ 8 \text{ if } \mu_7 < PROFIT_i^* \leq \mu_8 \\ 9 \text{ if } \mu_8 < PROFIT_i^* \leq \mu_9 \\ 10 \text{ if } \mu_9 < PROFIT_i^* \end{cases} \qquad (2.6)$$

The values of μ_i with $i = 1, \ldots, 9$ define the thresholds of the respective categories. Such models are commonly used for dependent categorical variables with unknown thresholds values. The fact that the questionnaire provides observable threshold parameters allows the identification of the variance which is usually unidentified. Consequently we can exactly quantify the marginal effects of the explanatory variables (Verbeek, 2004). This is in contrast to an ordered Probit model with unknown threshold values or a binary Probit model in which the estimated parameters are always scaled with the unidentified variance.[17]

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[16] A similar approach is used by Czarnitzki and Kraft (2010, 2012).

[17] See Verbeek (2004, pp. 205-207) for an illustrative example of an ordered Probit model with known threshold values.

I also test for additive groupwise heteroscedasticity within the sample using a likelihood ratio (LR) test. Heteroscedasticity may lead to inconsistency of the estimated coefficients. Therefore I model a heteroscedasticity term allowing the variance to vary by location in East Germany and industry affiliation. The location of the firm is captured by *EAST* while 10 industry dummies (*IND*) control for a firm's industry affiliation. The LR tests reject the hypothesis of homoscedasticity. Therefore, I will only present the estimation results of the heteroscedastic models.

Endogeneity issues may be of concern for the explanatory variables R&D intensity, market share and size as they may be determined simultaneously with profitability. I could not identify suitable instruments for these variables which would allow elimination of endogeneity. However, I can rule out short-term endogeneity as I lag the explanatory variables by 2 periods. Longer time lags or instruments would be needed in order to take account of long-term endogeneity, which are unfortunately unavailable.

In addition, I analyse correlations among the explanatory variables which should not affect the estimated coefficients, but may inflate the estimated standard errors. Both pair-wise correlations and variance inflation factors are calculated but there is no indication for multicollinarity issues when applying conventional standards from the relevant literature (Chatterjee and Hadi, 2006).[18]

2.1.5 Results

2.1.5.1 Descriptive statistics

Descriptive statistics of the full sample differentiated by a firm's R&D status are shown in Table 2.2. The share of R&D performers in the full sample is 59 %. It is apparent that in many aspects the group of R&D performers is similar to the non-R&D performers.

The mean profit of all groups of suppliers is between the categories 5 and 6 which imply return to sales between 2% to lower than 7%. The means for both groups are slightly higher in 2011 than in 2012. Between the groups there is however no large gap, even though the difference between R&D performers and non-performers is significant for 2011. The R&D performers have an average R&D intensity of 3.8 %. Taken together with the non-R&D performers the average R&D intensity drops to 2.3 % which is close to the 2.7 % reported in Czarnitzki and Kraft (2010) who use a similar dataset.

[18] The correlation matrix and the variance inflation factors can be found in Table A 5 in Appendix A.

Table 2.2: Descriptive statistics differentiated by suppliers' R&D status

	Full Sample		R&D performer		Non-R&D performer		T-test	
	Mean	SD	Mean	SD	Mean	SD		
PROFIT 2012	5.42	2.04	5.51	2.14	5.29	1.89	-1.15	
PROFIT 2011	5.69	1.97	5.85	2.03	5.46	1.86	-2.08	**
RDINT	2.26	5.20	3.81	6.31	0.00	0.00	-8.37	***
MSHARE	26.35	27.28	26.38	24.86	26.31	30.54	-0.03	
BUYCON	36.91	24.08	36.50	23.58	37.52	24.85	0.45	
SUBSTIT[a]	0.59	0.49	0.55	0.50	0.65	0.48	2.28	**
ELAST_L[a]	0.35	0.48	0.36	0.48	0.34	0.47	-0.49	
ELAST_M[a]	0.45	0.50	0.45	0.50	0.46	0.50	0.37	
ELAST_H[a]	0.11	0.32	0.11	0.31	0.11	0.32	0.13	
COMP[a]	0.49	0.50	0.52	0.50	0.44	0.50	-1.61	
DIVERS	33.20	24.59	36.18	24.06	28.86	24.77	-3.21	***
EXPORT	29.88	28.25	36.99	29.05	19.52	23.52	-6.92	***
SIZE	239.79	591.55	331.49	741.89	106.06	169.24	-4.14	***
FOREIGN[a]	0.10	0.31	0.12	0.32	0.08	0.28	-1.21	
EAST[a]	0.28	0.45	0.29	0.46	0.25	0.43	-1.02	
N	472		280		192			

[a] Dummy variable. Columns with heading SD display standard deviations. The last two columns display t-statistics whether a T-test on mean difference between the group of R&D performers and non-R&D performers rejects the Null hypothesis of no difference. The asterisks indicate the corresponding level of significance (* 10 %, ** 5 %, *** 1 %). The variable SIZE is presented in original values. Descriptive statistics of the remaining variables are presented in Table A 2 in Appendix A.

Non-R&D performers do not exhibit significantly lower market shares with the average market share being about 26 %. Also both groups do not differ in respect to the share of sales with the three largest customers. Across both groups the share of sales generated with the largest three buyers is between 37 and 38 %. The group of R&D performers exhibits a significantly lower share of firms indicating easy substitutability while there are no differences to non-R&D performers in the measures of the demand elasticity. This implies that even though the products of R&D performers are less easy to substitute, the demand elasticity limits the scope for quasi-monopoly pricing as otherwise buyers will go elsewhere. There is also no indication for R&D performers to be more frequently active in an oligopolistic market. Instead they are significantly more diversified, generate a much higher share of sales by exports and are also considerably larger compared to non-R&D performers. Both groups do not show any differences with respect to foreign ownership and location in Eastern Germany. The high overall share of firms located in East Germany (28%) is due to oversampling of these firms in the MIP.

Regarding the industries there are no surprises in the differences between R&D and non-R&D performing firms. The share of non-R&D performers is significantly higher in the Food/Tobacco, Textiles and Wood/Paper/Print industries while R&D performers constitute a significantly higher share in Chemicals, Machinery, and Electronics.

2.1.5.2 Regression results

I estimate equation (2.5) and present the results of the heteroscedasticity consistent ordered Probit model in Table 2.3. Columns I and II report estimation results for the profit in 2011 and the profit in 2012, without taking account of the interaction effects between R&D intensity and the variables indicating a supplier's bargaining power (*BUYCON* and *MSHARE*). The estimation results including interaction effects are presented in columns III and IV for the profit in 2011 and the profit in 2012 respectively.

Let us first have a look at the results without interaction terms in order to check how the buyer variables affect suppliers' profit (see Table 2.3, column I and II). The most important result is that a supplier's bargaining power does indeed affect his profitability significantly. As expected, the market share, as a measure of the strength of a supplier's market position and thus stronger bargaining power, exerts a positive effect on profitability. The share of sales with the largest three buyers, as a measure of buyer concentration and thus lower supplier bargaining power, does exert a negative effect on a supplier's profitability. The effects remain constant regardless the dependent variable. This supports the hypotheses 1 and 2, which state that higher buyer concentration should affect profits negatively, while a higher market share should have a positive effect on suppliers' profits.

Let us now turn to the results of the model including interaction terms between the variables reflecting the bargaining power of a supplier and R&D intensity (see Table 2.3, column III and IV). The results clearly show a positive relationship between bargaining power of the supplier and R&D investments. First, a higher market share, as a measure of the strength of a supplier's market position and thus its bargaining power, is related to larger R&D investments. Second, higher buyer concentration which indicates lower bargaining power of a supplier is connected with lower R&D investments. The highly significant interaction terms take explanatory power from the direct measures of *RDINT*, *MSHARE* and *BUYCON*. This demonstrates that profitability of R&D investments strongly depends on a supplier's bargaining position. A Wald-Test on the joint significance of *RDINT*, *MSHARE,* and *BUYCON* and their interactions rejects the hypothesis of all coefficients being jointly zero at the 5 % confidence level for the profit in

2011 and at the 1 % significance level for the profit in 2012. These findings support hypotheses 3 and 4.

Table 2.3: Estimation results of heteroscedasticity consistent ordered Probit models

	Dependent variable: Profit over sales							
	2011		2012		2011		2012	
	I		II		III		IV	
RDINT	-0.078		-0.104	*	-0.030		0.017	
	(0.062)		(0.060)		(0.110)		(0.108)	
MSHARE	0.023	***	0.023	***	0.016	*	0.015	*
	(0.008)		(0.008)		(0.009)		(0.009)	
BUYCON	-0.019	*	-0.021	**	-0.010		-0.008	
	(0.011)		(0.010)		(0.011)		(0.011)	
MSHARE x RDINT					0.007	***	0.007	***
					(0.002)		(0.002)	
BUYCON x RDINT					-0.007	**	-0.009	***
					(0.003)		(0.003)	
SUBSTIT[a]	-1.388	***	-1.379	***	-1.363	***	-1.358	***
	(0.514)		(0.499)		(0.512)		(0.496)	
ELAST_L[a]	-2.042	**	-2.811	***	-1.897	*	-2.592	***
	(0.995)		(0.978)		(0.989)		(0.971)	
ELAST_M[a]	-2.641	***	-2.880	***	-2.606	***	-2.782	***
	(0.982)		(0.954)		(0.979)		(0.948)	
ELAST_H[a]	-3.153	***	-3.626	***	-3.108	***	-3.510	***
	(1.137)		(1.122)		(1.129)		(1.107)	
COMP[a]	0.959	**	1.203	**	0.940	**	1.187	**
	(0.483)		(0.486)		(0.477)		(0.480)	
DIVERS	-0.013		-0.026	**	-0.013		-0.027	***
	(0.011)		(0.010)		(0.010)		(0.010)	
EXPORT	0.019	*	0.018	*	0.017	*	0.016	
	(0.010)		(0.010)		(0.010)		(0.010)	
SIZE	-0.151		-0.377	*	-0.133		-0.376	*
	(0.199)		(0.197)		(0.198)		(0.196)	
FOREIGN[a]	-0.51		-1.469	*	-0.444		-1.402	*
	(0.826)		(0.813)		(0.821)		(0.809)	
EAST[a]	0.447		0.236		0.629		0.439	
	(0.538)		(0.528)		(0.535)		(0.520)	
Constant	7.427	***	9.406	***	7.240	***	9.152	***
	(1.681)		(1.598)		(1.666)		(1.584)	
$ln\hat{\sigma}$	1.390	***	1.298	***	1.347	***	9.152	***
	(0.151)		(0.152)		(0.153)		(1.584)	
Industry dummies included	yes		yes		yes		yes	
Wald - Test: joint significance of industry dummies	31.45	***	39.97	***	33.60	***	43.64	***
$R^2_{McFadden}$	0.81		0.81		0.80		0.80	
N	472		472		472		472	
Log likelihood	-919		-916		-915		-910	
LR-test on heteroscedasticity	$LR\chi 2$ (11) = 49.95	***	$LR\chi 2$ (11) = 54.79	***	$LR\chi 2$ (11) = 50.91	***	$LR\chi 2$ (11) = 54.41	***

[a] Dummy variable. Standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Heteroscedasticity term includes East and 10 industry dummies. Estimation results of the industry dummies are presented in Table A 3 in Appendix A.

To get an idea about the magnitude of the effect of *RDINT*, *MSHARE*, and *BUYCON*, let us consider an average supplier among the group of R&D performers with group averages of market share (value equals 26 %) and buyer concentration (37 %). As a benchmark, unconditional profits over sales in the manufacturing sector are estimated, which were 5.5% in 2011 and 4.7% in 2012.[19] On average, an increase in R&D investments 2010 by one percentage point would reduce the average supplier's profit by 0.11 percentage points in in 2012.

In contrast, let us now consider the profitability of the same supplier if the largest three buyers account for 100 % of the sales. Then an increase in R&D investments in 2010 would reduce profitability in 2012 by 0.67 percentage points. Given the average profit of 4.7% in 2012 a reduction by 0.67 percentage points would decrease the profit over sales by about 14 %. This result highlights the substantial negative effects that may result from buyer concentration on supplier profitability. It indeed seems that suppliers facing low bargaining power in vertical relationships cannot fully appropriate the returns of their R&D investments.

For comparison let us consider the effect if the supplier is a monopolist, i. e. his market share is 100 %. Then an increase in R&D investments in 2010 would increase profitability in 2012 by 0.49 percentage points. This corresponds to an increase in profit over sales by 10 %.

With respect to the other explanatory variables influencing a supplier's profitability, I find across all specifications negative results for the substitutability of the produced good, the strength of the demand elasticity and oligopolistic competition which is in line with microeconomic theory. Given the results of the columns III and IV, if a supplier's product is easy to substitute, the return on sales is on average 1.4 percentage points lower when compared to suppliers who state that their products are not easy to substitute, all else equal. Similarly, an increase in demand elasticity from relatively inelastic to highly elastic implies ceteris paribus a reduction in profitability about 3.1 percentage points in 2011 and 3.5 in 2012. The profit in 2012 of suppliers which face oligopolistic competition in 2010 is on average 1.2 percentage points higher compared to suppliers who face more or less competitors.

[19] That was done by estimating an ordered Probit model with a constant only.

For the variables indicating the degree of diversification, the export intensity, the firm size and affiliation to a foreign enterprise group the results are not significant across all model specifications but the coefficients point into the same direction. All else equal suppliers with a more diverse product portfolio exhibit lower profits while exporters have larger profits. Firm size does negatively affect profitability as does the affiliation to a foreign enterprise group. The estimated coefficients of *EAST* are insignificant throughout all estimations.

Robustness Tests

It has been argued before that larger firms are likely to be more efficient, to have higher market shares and thus to be more profitable (see also subsection 2.1.4.2). In addition, as R&D intensity is defined as R&D expenditure over sales, smaller firms tend to have higher values of *RDINT* since their sales numbers are smaller compared to larger firms. This would result in higher values of *RDINT* for a given amount of R&D expenditure. Small sales numbers also promote high sales shares with the largest three customers. Therefore, one could presume that the negative effect of *RDINT* and *BUYCON* on profitability and also the negative interaction term between *RDINT* and *BUYCON* are mainly driven by small firms. In order to test for this, all firms having fewer employees than the firm on the 25 % quantil (value equals 23 employees) are excluded from the sample. As this reduces the small sample further to 357 firms, I drop the explanatory variables *COMP*, *EXPORT* and *SIZE* since a Wald-test on joint significance could not reject the Null hypothesis of these coefficients being jointly zero. Moreover, I restrict myself to the presentation of estimations using the profit in 2012 as dependent variable in Table 2.4 for reasons of simplicity.

The results show that in the model specification without interaction terms the coefficients of *RDINT* and *BUYCON* turn insignificant. In contrast, all variables indicating substitutability and demand elasticity are highly significant and in about the same magnitude as in the estimations with the full sample. Inclusion of the interaction terms shows however that the interaction term of *BUYCON* and *RDINT* loses statistical significance as well, while the interaction term of *MSHARE* and *RDINT* more than triples in magnitude from 0.007 in Table 2.3 (column IV) to 0.023 in Table 2.4 (column II).

Table 2.4: Estimation results of heteroscedasticity consistent ordered Probit models for a sample excluding small firms and a sample of R&D performing firms

	Dependent variable: Profit over sales 2012							
	Small firms excluded				R&D performing firms			
	I		II		III		IV	
RDINT	0.036		-0.166		-0.070		0.097	
	(0.080)		(0.131)		(0.069)		(0.129)	
MSHARE	0.037	***	0.014		0.054	***	0.040	**
	(0.009)		(0.010)		(0.014)		(0.016)	
BUYCON	-0.013		-0.005		-0.012		0.013	
	(0.012)		(0.013)		(0.014)		(0.017)	
MSHARE x RDINT			0.023	***			0.006	**
			(0.004)				(0.003)	
BUYCON x RDINT			-0.007	**			-0.009	***
			(0.003)				(0.003)	
SUBSTIT[a]	-1.57	***	-1.507	***	-1.629	***	-1.472	**
	(0.528)		(0.510)		(0.614)		(0.618)	
ELAST_L[a]	-2.547	**	-2.485	**	-0.629		-0.921	
	(1.052)		(1.018)		(1.434)		(1.444)	
ELAST_M[a]	-2.983	***	-3.119	***	-1.422		-1.877	
	(1.026)		(0.988)		(1.322)		(1.345)	
ELAST_H[a]	-3.077	**	-3.391	***	-2.713	*	-3.049	*
	(1.232)		(1.185)		(1.627)		(1.651)	
DIVERS	-0.025	**	-0.025	**	-0.034	**	-0.031	**
	(0.011)		(0.011)		(0.014)		(0.014)	
EXPORT					0.024	**	0.022	**
					(0.011)		(0.011)	
FOREIGN[a]	-1.673	*	-1.862	**				
	(0.861)		(0.858)					
EAST[a]	-0.672		-0.255		0.227		0.398	
	(0.561)		(0.539)		(0.725)		(0.716)	
Constant	8.439	***	8.824	***	4.589	**	4.354	**
	(1.547)		(1.513)		(2.117)		(2.121)	
$ln\hat{\sigma}$	1.543	***	1.493	***	2.262	***	2.148	***
	(0.177)		(0.178)		(0.363)		(0.352)	
Industry dummies included	yes		yes		yes		yes	
Wald - Test: joint significance of industry dummies	26.02	**	32.28	**	21.44	**	20.73	**
R^2_{McFadden}	0.52		0.75		0.59		0.65	
N	357		357		280		280	
Log likelihood	-687		-670		-530		-526	
LR-test on heteroscedasticity	$LR\chi2$ (11)= 38.56	***	$LR\chi2$ (11) = 37.49	***	$LR\chi2$ (16) = 68.91	***	$LR\chi2$ (16) = 66.64	***

[a] Dummy variable. Standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Heteroscedasticity term for the sample in columns I and II includes East and 10 industry dummies while it includes 5 size dummies, East and 10 industry dummies for the sample in columns III and IV. Estimation results of the industry dummies are presented in Table A 4 in Appendix A.

Therefore it seems that small firms indeed have a strong impact on the empirical analysis of bargaining power and the profitability of R&D. However, excluding them from the sample still shows the effect of bargaining power on R&D profitability. The Wald-Test on joint significance of *RDINT* and both interaction terms is rejected to the 0.1 %

confidence level. For the average R&D performing supplier this implies that with a buyer concentration of 36 % and a market share of 26 %, a one percentage point increase in R&D investments in 2010 would now increase profitability by 0.68 percentage points whereas the estimate with the full sample predicted a reduction of 0.36.

The average of the unconditional profit distribution in this sample of firms equals 4.5 %. The increased coefficient of the interaction between *RDINT* and *MSHARE* implies, that a percentage point increase in R&D intensity in 2010 would increase profitability for the average R&D performing supplier in 2012 by 0.18 percentage points. The corresponding effect for a monopolist with average buyer sales share is 1.9 while the fully dependent supplier with an average market share experiences a drop in profits by 0.3 percentage points. This corresponds to an increase in profits of 43 % and a decrease of 7 % respectively.

Strongly related to the size of a firm is the likelihood of being a R&D performer. Hence one could argue in a similar vein, that non-R&D performing firms drive the results from the full sample since they are less competitive and therefore hold lower market shares. Hence, the positive effect of *MSHARE* on profitability could be caused by non-R&D performers which in addition may also affect the positive slope of the interaction term between *MSHARE* and *RDINT* since they have a R&D intensity of zero.

To check this, all non-R&D performing firms are dropped. As the number of observations drops to 280, the number of explanatory variables is reduced. *COMP*, *FOREIGN* and *SIZE* are excluded after the Wald-Test rejected that all three coefficients together are jointly significant. The results are presented in Table 2.4 columns III and IV.

In the specification without interactions the same pattern emerges as if all small firms were dropped. That is, *RDINT* and *BUYCON* turn insignificant. If the interaction terms are included, the interaction between *RDINT* and *MSHARE* loses a level of significance while the other cross term is strongly significant but does not substantially increase in magnitude. Notice instead, that the exclusion of the non-R&D performing firms drove the confidence levels of the demand elasticity coefficients either insignificant or close to insignificance. Hence, it seems that within the group of R&D performers demand elasticity is not as important in determining profitability as in a sample including non-R&D performers as well. In this sample the average estimated unconditional profit over sales in 2012 is 5 %. A percentage point increase in R&D investments 2010 would decrease profitability of the average R&D performing supplier with a buyer concentration of

36 % and a market share of 26 % by 0.05 percentage points on average. This corresponds to a 1 % decrease in profits. This is considerably lower than in the full sample. The effect for a monopolistic supplier is again positive. A percentage point increase in R&D intensity 2010 would increase profitability by 0.4 percentage points and corresponds to an increase in profits by 8 %. Contrastingly, a fully dependent supplier, i. e. with a share of sales by the largest three buyers of 100 %, would experience a drop in profitability 2012 by 0.61 percentage points due to a percentage point increase in R&D intensity 2010. This implies a profit loss of about 12 %.

2.1.6 Concluding remarks

Section 2.1 explores the effect of bargaining power in vertical relationships on the profitability of suppliers' R&D investments. Studies on the relationship between R&D, innovation and firm profitability mostly concentrate on the impact of horizontal market structure which follows traditional industrial organization literature that emphasizes the importance of market concentration and entry barriers for firm profitability. While providing inconclusive results, none of the existing studies takes vertical interactions of R&D performers into account.

Building on theoretical and empirical evidence about the effects of bargaining power in vertical relationships on a supplier's profitability, the crucial determinants of a supplier's bargaining power are identified as the market position and the degree of concentration in the buyer portfolio. With respect to R&D profitability the latter is expected to diminish returns from R&D, while the former is expected to increase it.

The hypotheses are tested using a sample of 472 German firms from manufacturing sectors. The empirical findings support all hypotheses and therefore highlight the importance of taking bargaining power occurring in vertical relationships into account when measuring R&D profitability. The estimated effects are considerable: for an average R&D performing supplier an increase of R&D intensity in 2010 by a percentage point would reduce profits by about 14 % in 2012 given the supplier depends completely on the largest three buyers and does hold an average market share. Contrastingly, a monopolist R&D performing supplier with average buyer concentration would experience a profit increase by 10 % in 2012. What is more, the findings support the hypothesis of a lagged impact of R&D investments on a supplier's R&D profitability (Ravenscraft and Scherer, 1982).

The findings are an important contribution to the existing literature for several reasons. First, because this is the first study that analyses the effects of supplier's bargaining power on the profitability of R&D. Second, the sheer magnitude of the effects indicates that further research with respect to the R&D incentives for suppliers facing bargaining power is needed.

There are opportunities for improvement – both theoretically and empirically – which are left to future research. From a theoretical point of view, it would be useful to have a model explaining how R&D incentives are shaped by bargaining. Therefore, R&D should be integrated in the existing bargaining framework as it was pioneered by the model of Inderst and Wey (2007). In addition, bargaining models concerned with buyer power are often limited to monopoly in the supply market and separate downstream markets. It would be useful for empirical purpose – and especially for the question how bargaining power affects R&D profitability – if upstream competition is introduced.

Empirically, it would be worthwhile to gather information for each of the suppliers' buyers instead using aggregated shares. In contrast to this study, it would allow the generation of buyer-specific outside option values. In addition, it would help to have information on all products which are supplied to the buyer and the respective market share of the supplier in all according markets. With that information it would be possible to render a suppliers' outside options even more precisely. Moreover, it would be interesting to collect information about factors which are likely to determine the buyers' outside options, e. g. the share of inputs sourced from a particular supplier, product markets the buyers are active in, the concentration level in the respective market and so on. Thus, more information on the nature of the buyers would be invaluable and would allow for the analysis of countervailing power for instance (Galbraith, 1956). Finally, it may be helpful to have data on vertical relationships over a longer period of time. This would improve on one hand the analysis of the interaction between suppliers' R&D activities and their bargaining power as there may be a considerable time lag between the implementation of successfully developed products or production technologies and their impact on suppliers' bargaining power. On the other hand observations of vertical relationships over a longer time period would also allow for an analysis of effects emerging from downstream activities e. g. increasing concentration through merger, firm entries or exits.

2.2 Buyer power and suppliers' incentives to innovate[20]

2.2.1 Introduction

The impact of market structures on innovation activities has received much attention in innovation research. The vast majority of the literature concentrates on the effects of horizontal competition on innovation incentives and neglects the incentives resulting from vertical interactions in markets. With many industries experiencing concentration processes suppliers are often confronted with powerful buyers. Yet, relatively little is known about how powerful buyers may affect innovation incentives of upstream firms. A common belief is that exertion of buyer power negatively affects innovation decisions of suppliers because buyer power will lead to decreasing profits of suppliers, which at the same time lowers their investment incentives. This is expected to reduce the variety in suppliers' range of products (OECD, 1998; European Commission, 1999a; Inderst and Shaffer, 2007). However, recent theoretical findings suggest that buyer power might have positive impacts on suppliers' innovation incentives (Inderst and Wey, 2007; Inderst and Wey, 2011).

So far, the role of suppliers' innovation incentives in the presence of powerful buyers has been discussed largely from a theoretical perspective.[21] Moreover, theoretical results on the effect of buyer power on suppliers' innovation incentives are inconclusive. From an empirical point of view, only a few studies exist that analyse suppliers' incentives to innovate when facing a powerful buyer. These studies often lack an objective measure for buyer power on firm level but rather use either aggregated industry measures or firms' subjective assessment whether they are confronted with powerful buyers. Furthermore, analyses of the relationship between buyer power and suppliers' incentives to innovate are mostly focused on particular industries which are perceived to be heavily affected by concentration processes among buyers. Besides, all these studies tend to neglect the impact of buyer market characteristics.

For our empirical study we make use of a dataset containing 1,036 observations from German firms across manufacturing and service sectors based on the German Innovation Survey. It contains rich information on aspects of bargaining power in vertical rela-

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[20] An earlier version of section 2.2 has been published as ZEW Discussion Paper: Köhler, C. and C. Rammer (2012), *Buyer power and suppliers' incentives to innovate*, ZEW Discussion Paper 12-058.

[21] For a comprehensive review of the theoretical development on buyer power see e. g. Inderst and Mazzarotto (2008).

tions and suppliers' innovation activities. In contrast to existing studies the dataset enables us to apply objective measures for buyer power. What is more, we are able to differentiate different degrees of buyer power which is a further novelty of this study. Competition and technology intensity in buyer industries are likely to impact suppliers' innovation incentives as well. Thus our study takes these downstream characteristics into account and provides a first attempt to explore joint effects between buyer power and downstream industry environment. Finally, we contribute to the literature by disentangling the effects of buyer power on the suppliers' innovation incentives into the effect on the decision to start innovation activities and the effect on the amount of resources spent on innovation.

Section 2.2.2 reviews the theoretical literature on the effects of buyer power on suppliers' innovation incentives while section 2.2.3 provides an overview of existing empirical literature in this context. The following section presents the data, the variable specification and our estimation strategy. Descriptive statistics as well as estimation results and robustness checks are presented in section 2.2.5 while section 2.2.6 provides first evidence on the joint effects of buyer power and downstream industry characteristics. Section 2.2.7 concludes and offers possible ways for further research.

2.2.2 Theoretical framework

Literature provides different approaches to the emergence and impacts of buyer power. In contract theory it is assumed that supplier and buyer negotiate bilaterally over prices and quantities of the respective good or service to be traded. Given that contracting between the supplier and the buyer leads to joint profit, the split of the profit then depends on the bargaining position of each contracting party. The strength of the bargaining position and hence bargaining power is determined by the profits to be realised when the contract is made with an alternative supplier or buyer. The higher such disagreement or outside-option payoffs in relation to the counterparts payoffs the stronger the bargaining position of the respective contractor. According to this approach, buyer power results from the fact that more valuable outside options are at the disposal of the buyer thereby allowing the buyer to extract a larger share of joint profits (Inderst and Valletti, 2007; Dobson and Inderst, 2008). In this paper we adopt the view of buyer power being a consequence of bargaining power exerted by the downstream firm (buyer) on the upstream firm (supplier) (Dobson and Inderst, 2008; Inderst and Mazzarotto, 2008).[22]

When deciding on investment in innovation efforts a supplier will consider the discounted value of future rents collectable from this activity and whether these rents are appropriable. Given that buyer power results from a stronger bargaining position of the buyer relative to the supplier, the effect of buyer power on suppliers' innovation incentives seems to be clear-cut: When facing powerful buyers, the supplier has less incentive to innovate, as the appropriability of innovation rents is too low. Recent theoretical studies show, however, that buyer power may provide additional innovation incentives for suppliers. Suppliers facing large buyers have an incentive to invest in both product and process innovations, given that size is the sole source of buyer power (Inderst and Wey, 2007). While process innovation allows lower unit costs at high volumes compared to a supplier facing many smaller buyers, product innovation renders higher revenues compared to the old product. Either way, supplier innovation leads to a devaluation of the buyer's outside options and in turn strengthens the bargaining position of the supplier allowing for a larger share of joint profits.

Given the life-cycle hypothesis of Utterback and Abernathy (1975), a positive effect of buyer power on suppliers' innovation incentives might also occur since suppliers with few buyers may suffer less from uncertainty over innovation demand of buyers and therefore have a declined risk of innovation failure (Klepper, 1996). In addition, a larger size of orders might induce higher incentives for suppliers to engage in R&D as there is more certainty in the sales of new products (Peters, 2000).

In contrast, merger in buyer markets may reduce incentives for product differentiation by suppliers. Product differentiation is often linked to innovation since entering new product markets typically constitutes an innovation activity. In case of a buyer merger, the consolidated buyer may be better off using a single sourcing strategy, i.e. to stock only goods of one supplier. If the likelihood of a buyer merger is increasing, this strategy will lead to a lower degree of product differentiation of suppliers (Inderst and Shaffer, 2007). Large buyers may have an incentive to force their suppliers into contracts which constitute an exclusive relationship between supplier and buyer. Such supply

[22] One could also study buyer power in the framework of monopsonistic behaviour (see e. g. Mas-Colell et al., 1995). The main argument of this approach is that monopsonistic firms strategically reduce demand in order to maximise profits. However, this may not apply for most supplier-buyer relationships.

contracts will reduce upstream innovation incentive because suppliers will bear disadvantages of low-scale production and have less incentive to innovate (Stefanadis, 1997). What is more, larger buyers can more credible threat to integrate backwards and may intensify competition on supplier markets (Katz, 1987). By breaking up collusion among suppliers they lower suppliers' profits (Scherer and Ross, 1990). This effect is increasing in the size of the buyer (Snyder, 1996; Snyder, 1998). Also, they are in a position to alleviate market entries on the supply side, e.g. by overtaking fix costs of otherwise unprofitable entrants or pre-committing some of their purchases (Dobson and Inderst, 2008).

The concern about negative effects of buyer power on innovation incentives of suppliers led the UK Competition Commission (CC) to conduct a market investigation focusing on adverse effects on competition in the supply for groceries in the UK due to the behaviour of retailers. One part of the investigation examined whether buyer power of retailers may "impose excessive risks and unexpected costs on suppliers, which reduces suppliers' incentive or ability to invest and innovate. This could lead to reduced capacity, reduced product quality and fewer new product offerings" (Competition Commission, 2008; p. 157). Although the CC did not find evidence that UK grocery suppliers exhibit less innovation efforts, they expect the innovation performance to be decreasing in future if consequences of buyer power, e.g. retrospective price adjustments or excessive transfer of risks, continue at the observed level (Competition Commission, 2008; p. 173).

The results of recent theoretical literature regarding the impact of buyer power on suppliers' innovation incentive are inconclusive. Hence, the question how buyer power affects a supplier's innovation incentives can only be answered empirically. Therefore, we formulate two rivalling hypotheses:

Hypothesis 1a: *Buyer power will positively affect the innovation incentives of a supplier.*

Hypothesis 1b: *Buyer power will negatively affect the innovation incentives of a supplier.*

2.2.3 Earlier Research

Empirical studies frequently find a negative relationship between buyer power and innovation activities of suppliers. Existing studies follow quite different approaches to capture buyer power and innovation incentives of suppliers. Farber (1981) analysed the effect of market structure in the buyer market on R&D efforts in supplier industries using cross-sectional industry level data of 50 4-digit manufacturing SIC-industries from the US. Market structure in both supplier and buyer markets is measured by concentration ratios, reflecting the share of industry sales generated by the four largest enterprises. Employing a simultaneous equation model which explains the share of scientists and engineers in the workforce, the advertising intensity and the seller concentration rate, he finds evidence that concentration in the buyer market affects R&D incentives of suppliers. The sign of this effect depends on the concentration in the supplier market. If the supplying industry is weakly concentrated, an increase in concentration of the buyer industry will have a negative effect on the share of scientists and engineers in the workforce. Conversely, this effect is positive if the market concentration in the supplier industry is sufficiently high.

The findings are in line with the results of Peters (2000) who investigates the effect of market structure in the buyer market both on suppliers' innovation inputs and innovation outputs using firm level data consisting of 401 German automotive suppliers. Innovation inputs are measured by R&D expenditure divided by sales as well as by total innovation expenditure divided by sales.[23] Innovation output is captured by the introduction of product or process innovations within a two year span. Market structure in the buyer industry is represented by the industry's concentration ratio (CR3) and by an additional dummy variable indicating whether the supplier has 10 or more customers. Regarding innovation intensity, the result indicates that firms supplying to highly concentrated buyer industries exhibit lower levels of innovation intensity. The negative correlation is mitigated, however, if suppliers are operating in a concentrated industry. With respect to R&D intensity, market structure in the buyer industry is found to moderate the effect of market structure in the supplier industry. Suppliers operating in a concentrated industry and supplying highly concentrated buyer industries exhibit a significantly higher R&D intensity. Conversely, suppliers operating in a concentrated industry and supplying buyer industries with a low degree of concentration show significantly lower R&D intensities. There is no evidence that the market structure of buyer industries has a significant impact on the supplier's probability to introduce new products. Also, the supplier's

[23] Innovation expenditure includes expenses not only for R&D but also for other activities aiming at the introduction of new products or processes, such as design, marketing, training and purchase of machinery, equipment, software and intellectual property.

probability to introduce process innovations is not affected by the concentration in the buyers industry but by the number of customers.

Weiss and Wittkopp (2003a; 2003b) use survey data from German food manufacturers. Innovative activity is measured by the overall number of new products introduced within a three year time span (Weiss and Wittkopp, 2003b) and by the number of new products with either regular or superior quality introduced within a three year time span (Weiss and Wittkopp, 2003a). Market power of the retailers is captured by firms' assessment whether retailers are able to exert pricing pressure on them on a scale ranging from 1 (very low) to 5 (very high). Using a small sample of 88 and 87 firms, respectively, they observe that suppliers experiencing very high pricing pressure of retailers introduce significantly less new products. With respect to quality differences among the newly introduced products they yield mixed results. While they observe a negative relationship between retailers' pricing pressure and the number of new products with regular quality, retailers' pricing pressure does not have a significant effect on the number of new products with premium quality.

2.2.4 Empirical study

2.2.4.1 Data

The empirical part of our study employs firm level information from the MIP which consists of a representative stratified random sample of German firms. Data collection is carried out by the ZEW on behalf of the Federal Ministry of Education and Research. The MIP provides annual information on innovative behaviour in the German manufacturing sector since 1992 and in the service sector since 1994 and is at the same time the German contribution to the European CIS. Definitions of innovation and innovative activities are taken from the OECD’s Oslo Manual. The target population of the MIP are enterprises located in Germany with at least five employees.[24]

The survey wave 2005 of the MIP offers unique information on firms' market environment, their R&D spending, R&D cooperation and several other informations which are described in more detail in the following section. The wave 2005 is merged with data from the survey wave 2006 to observe innovation behaviour of firms in the following period. Since we are interested in business-to-business relationships, we drop all obser-

[24] For a more detailed description of the MIP see Peters (2008) and Peters and Rammer (2013).

vations of firms indicating that private households or public institutions are the largest customers. Additionally, we exclude firms from the sectors energy, mining, recycling, sewage and radio and television as firms in these sectors may behave significantly different in terms of investment behaviour due to strong regulations. Moreover, firms supplying R&D services are usually small but exhibit high R&D intensities and supply few firms. As they conduct R&D not necessarily for own purpose but on behalf of their contractors we exclude them as well. After removing all outliers and deleting all observations with missing values in the variables required to estimate the model, we eventually arrive at a sample of 1,036 firms representing the Nace 2-digit industries 15-22, 24-36, 51, 60-67, 72 and 74.[25]

2.2.4.2 Variables[26]

2.2.4.2.1 Innovation incentives

A number of authors have proposed different concepts for measuring innovation activities.[27] Since we are interested in innovation incentives we choose an input measure as a proxy, as it represents discounted future rents attached to innovative efforts no matter whether these efforts are successful. We use the R&D intensity (*RDINT*) which is defined as the expenditure on R&D activities divided by employees. It is widely used as measure of innovation input in the literature (see e. g. Cohen and Levin, 1989; Crepon et al., 1998). As a large share of firms does not have any R&D expenditure the distribution of the R&D intensity is heavily skewed. In order to normalize it, the logarithm is taken, i. e. R&D intensity enters the estimation in logs.

2.2.4.2.2 Buyer power

Our main explanatory variable of interest is buyer power. As we define buyer power to result from a relatively stronger bargaining position of the buyer compared to the supplier, we have to construct a measure which captures whether a supplier is confronted with buyer power or not. One of the factors determining a supplier's bargaining position is the share of sales generated by one buyer, as this can indicate substantial economic dependency. Once "a buyer accounts for sufficiently large fraction of a supplier's overall

[25] Nace is the industrial classification system used in European Union statistics. This chapter makes use of Nace Rev. 1.1. The breakdown of industries is presented in Table B 1 in Appendix B.2.
[26] For an overview of all applied variable definitions see Table B 2 in Appendix B.2.
[27] For an overview see Haagedorn and Cloodt (2003).

business, this may lead to a more-than-proportional reduction in the value of the supplier's profits outside a relationship with the particular buyer" (Dobson and Inderst, 2008; p.339). This is due to the fact that in case the supplier loses the contract with the buyer, the supplier's economic viability could be undermined. Losing a large contract will result in free capacity on the supplier's side and will require the supplier to significantly lower prices in order to sell the excessive capacity to remaining buyers (Inderst and Wey, 2007). Therefore, our measure includes the extent to which a supplier's sales depend on the three largest customers. Section 2.1 provides evidence, that this measure is correlated with lower profitability of suppliers. Hence, suppliers with a concentrated buyer structure may suffer from the exertion of buyer power.

The degree to which a supplier is confronted with buyer power also depends on the buyer’s opportunities to switch to another supplier. The ease of switching is determined by the market structure in the supply market on the one hand and the substitutability of the demanded product on the other. A monopoly in the supply market does not allow for an outside option of the buyer, resulting in a powerful bargaining position of the supplier, even if the buyer is a monopsonist.[28] Conversely, a polypolistic supply market and a monopsonistic buyer market enable the buyer to behave opportunistically and might lead to hold-up (Klein et al., 1978). That is, after the supplier carried out necessary investments to fulfil contracted obligations, the buyer may initiate ex-post negotiations and force the supplier to accept conditions which reduce profit margins or even lead to losses (Williamson, 1975). Thus, our measure has to include information about the concentration in the supplier's market and the substitutability of the supplied products.

We consider different degrees of buyer power and subsequently define two measures (see Table 2.5) combining information from several questions in the survey 2005. First, we use a question on the share of sales with the three largest customers which was surveyed as a categorical variable. Categories were defined as less than 20 %, 20-49 %, 50-99 % and 100 %. Another categorical variable we make use of is the number of competitors in the supplier’s main market. Here categories were defined as none, 1-5, 6-15 and more than 15. Finally, we use the supplier’s assessment whether products of competitors are easy to substitute with own products. The statement was given with a 4-point-Likert

[28] Such circumstances, characterized by highly concentrated markets on both sides, have been described as a countervailing power situation by Galbraith (1956).

scale allowing to choose between the assessments “fully applies”, “somewhat applies”, “applies very little” and “applies not at all”.

Table 2.5: Definitions of buyer power measures

Measure of buyer power	Share of sales generated with the three largest customers		Number of a supplier’s competitors		Degree of substitutability of a supplier’s product
BP_L	≥50%				
BP_H	≥50%	AND	>5	OR	High substitutability (agree, fully agree)

Our first measure for being exposed to buyer power (*BP_L*) is a dummy variable reflecting the fact that the three largest customers of a supplier account for 50 or more percent of the sales. We interpret this as a degree of buyer concentration which could seriously undermine the economic viability of a supplying firm.[29] Hence it is included in all two measures of buyer power. Our second measure (*BP_H*) equals *BP_L* but takes unit value only, if additionally the supplier has either more than 5 competitors or products are easy to substitute. Compared to *BP_L*, this definition reflects an even weaker bargaining position of the supplier since it not only covers concentration in terms of sales but also a buyer’s opportunities to switch to other suppliers. Accordingly, we expect a stronger effect of *BP_H* on a supplier’s incentive to innovate compared to *BP_L* as it captures buyer power even more precisely.[30]

Note that this operationalization of buyer power deviates in two important ways from existing studies. First, it measures the impact of buyer concentration on firm level and not on industry level as it is the case in most other studies (Farber, 1981; Peters, 2000). This is an important distinction because it may be sufficient for the execution of buyer power to have a large share in the business of the supplier regardless of the concentra-

[29] One might object that this measure is not providing a sufficiently accurate degree of buyer power, as the share of sales generated by the largest single customer could be considerably lower. Given that the largest three buyers contribute equal shares, the smallest possible share generated by one buyer is roughly 17%. If they contribute unequal shares of sales, than at least for one buyer the share must be higher than 17%. In the merger case Rewe/Billa and Meinl, the European Commission established that a supplier whose business with the two merging chains accounted for more than 22% has to be considered as "economically dependent" on them. A survey among grocery producers provided evidence that this was the most suppliers could afford to lose without a serious danger of bankruptcy. Hence, we consider our measure to be sufficiently precise in order to correctly reflect serious economic dependency from buyers (European Commission, 1999b).

[30] Note that if supplier and buyer cooperate for R&D, it is likely that we observe high R&D expenditure together with a high buyers’ sales share. This would lead to biased results as we are interested in the effect of buyer power outside of R&D cooperation. Hence, we exclude all firms which indicated to have R&D cooperation with customers.

tion in the buyer industry. This is highlighted by the results presented in section 2.1 which show that buyer concentration has an adverse effect on firms' profitability. Second, our measure is likely to be more objective than measures from other studies based on survey data (e.g. Weiss and Wittkopp, 2003a; 2003b) which exploit information from a question asking for the supplier's assessment on retailers' market power or pricing pressure. In contrast to existing studies the richness of our dataset allows the exploration of different degrees of buyer power. Therefore, our analysis provides a valuable contribution to the empirical literature on buyer power and supplier's innovation incentives. Finally, our study builds on a sample of firms from various industries, while the firm-level studies of Peters (2000) and Weiss and Wittkopp (2003a, 2003b) deal with suppliers in a particular industry.

2.2.4.2.3 Competition and R&D intensity in the buyer's industry

It is likely that R&D incentives provided by powerful buyers differ according to characteristics of the industry they are active in.

An important attribute of the buyer's industry to affect suppliers' R&D incentives is the intensity of competition. Recall that according to the bargaining literature the joint profit is the sum of the downstream and the upstream profit generated by the contract between supplier and buyer (e. g. Chipty and Snyder, 1999). If competition in the downstream market is strong, margins in the downstream market are low.[31] Holding the upstream profit constant, this implies that the joint profit shrinks. Hence, the profit of a supplier from the contract with a buyer under intense competition will be lower. Under such circumstances the expected rents of innovating may be too small to induce R&D investments on the suppliers' side, especially against the background of high uncertainty and the financial burden attached to an innovation project. One could therefore expect a negative effect of strong downstream competition on suppliers' innovation incentive.

On a different note, high downstream competition can also lead to increasing downstream demand for innovative products which allows the buyer to gain a competitive advantage over competitors. That is, buyers in very competitive markets may be willing to invest into intermediary products allowing them to lower the costs of production and distribution, to differentiate away from competitors or to enter new markets. According to the demand-pull hypothesis this attracts also innovations directed towards such de-

[31] This holds no matter whether competition is a la Bertrand or Cournot.

mand (Schmookler, 1966; Scherer, 1982b). This would imply a positive effect of strong downstream competition on suppliers' innovation incentive.

Besides downstream competition intensity, supplier's R&D incentives should also be affected by the buyer's R&D intensity. If competition in the downstream market is driven by technology development, buyers are urged to invest heavily into the development of new products and new process technology. This in turn, reduces their profits. In the context of patent races, some part of this investment may not be turned into commercial success but is sunk hurting profits further (Fudenberg et al., 1983). Given bargaining over the joint profit between supplier and buyer, this would again imply a negative effect which is similar to the argumentation regarding the impact of strong competition. Additionally, the start of own R&D activities often requires considerable investments due to a minimum size of such projects. The minimum size of projects aiming at the supply of R&D intensive industries may well be larger, thereby lowering the incentives to start R&D activities at all, given the risk, uncertainty and high cost attached to them. In contrast, demand-pull due to high investments in R&D may have a positive effect on suppliers' R&D incentives.

Hence, it is necessary to control for differences in the buyers' industries with respect to both competition and R&D intensity. To derive measures for the intensity of competition and R&D in the buyer market, it is desirable to have information about the identity of the most important buyers. Such data is extremely difficult to obtain through voluntary surveys since most firms will refrain from disclosing such information, and sometimes confidentiality agreements with buyers restrict disclosure at all. In the MIP survey 2005, firms were asked to name the sector of the largest three customers. Questionnaire instructions helped firms to provide buyer sector information that corresponds to a Nace 3-digit level, though firms did not give industry codes but a short description of sectors which have been coded to Nace 3-digits. Based on this sector information, we construct industry level measures of competition. For the degree of competition intensity we use an industry's price cost margin (*BUYPCM*) since it gives an indication whether firms are able to achieve margins high above their marginal costs. For the sake of interpretation, we transform the variable to 1–PCM, i.e. values close to zero indicate low price competition in the buyer market and values close to one refer to very intense price competition. As an indicator of technological competition we use a sector's R&D intensity (*BUYRDINT*: R&D expenditure over sales) since firms will dedicate a higher share of their resources to R&D if keeping pace with technological change is crucial for competing within the market.

We do not have information on the location of the largest buyers which implies that we do not know whether they are domestic or international buyers. We do know the firms' export share in total sales however. Thus, we calculate both *BUYPCM* and *BUYRDINT* for Germany and for OECD countries, to capture the intensity of competition and R&D on domestic and foreign markets. We weight the values by the respective share of a supplier's domestic and international sales.[32] In addition, we also introduce dummy variables indicating the position of the buyer industry in the value chain (*BUYIND*). We distinguish between the production of raw materials, intermediaries, capital goods, consumer goods, producer services and consumer services.[33]

2.2.4.2.4 Competitive environment of the supplier

A supplier's incentive to invest in innovation activities may be shaped by the competitive environment in their own market as well. Therefore, we control for concentration in the supplier's market since a monopoly or oligopoly may allow for higher margins and thus for higher investments in R&D or conversely for lower incentives to invest in R&D.[34] Concentration in the supplier's market is measured by two dummy variables capturing the number of main competitors. The first dummy takes the value one if the firm responded to have no competitors and zero otherwise (*NOCOMP*). The second dummy takes the value one if the firm indicated to have at most 5 main competitors and zero otherwise (*COMP*). For descriptive purposes we construct a dummy variable for the reference category of firms with 6 or more competitors (*COMP6+*).

What is more, a high degree of product diversification offers more outside options to the supplier. Hence the degree of a supplier's product diversification is included, measured as the share of sales which is not generated by a supplier's main product line (*DIVERS*).

2.2.4.2.5 Further control variables

Following the literature on firms propensity to innovate (see e. g. Cohen, 1995; Crepon et al., 1998), we also include firm size measured by the number of employees in logs

[32] For a detailed description of buyer market measures see Appendix B.1.

[33] The definition of the industry groups can be found in Table B 3 in Appendix B.2.

[34] For an overview of the extensive literature dealing with the effects of market structure on innovation see e.g. Cohen (2010).

(*SIZE*), firm age in logs (*AGE*) and whether a firm belongs to an enterprise group (*GROUP*) as explanatory variables. Moreover, we also control for a firm's sector affiliation (*IND*) and whether a firm is located in East Germany (*EAST*).

2.2.4.3 Estimation strategy

Innovation incentives of suppliers are shaped by a supplier's bargaining position vis-à-vis its buyers and by the characteristics of buyer industries. Accordingly, we model the innovation decision of a supplier to be dependent on a measure reflecting the supplier's bargaining position, the attributes of downstream industries and further determinants. Since we measure innovation incentives by R&D intensity, we have to take a possible selection bias into account as this variable is only observable for firms that engage in research and development activities. To control for this we apply the well-known generalised Tobit model (Heckman, 1979).

This approach furthermore enables us to separate the effect of buyer power and buyers' industries' characteristics on the supplier's probability to start R&D activities from the effect on the decision on how much to invest in R&D once the supplier decided to start R&D. This constitutes an interesting extension to existing studies on this topic.

As many authors point out, when using a generalised Tobit model one needs to make sure to have an exclusion restriction which explains the selection but not the structural equation and is not correlated to the error term of the latter. We use firm size as exclusion restriction for several reasons. First, there are numerous studies which find that firm size will positively affect the probability to start R&D activities as larger firms have an advantage in spreading the fixed costs of R&D over larger output.[35] Second, empirical research on the relationship between firm size and R&D efforts among R&D performers shows that a linear relationship between R&D expenditure and firm size fits data mostly best (Bound et al., 1984; Cohen et al., 1987; Scherer, 1984). This implies a proportional relationship between firm size and R&D which should disappear if R&D intensity is scaled by size. Third, related research frequently uses firm size as an exclusion restriction in this context (see e. g. Griffith et al., 2006a).[36]

[35] This reason corresponds to stylized fact 1 presented in Cohen and Klepper (1996). See also the references cited therein.

[36] We also experimented with the inclusion of the firm size in the structural equation but it turned out that for each model specification the estimated coefficient of size is insignificant while the other coefficient estimates do not change substantially.

In the first stage we estimate the probability of a supplier to spend a positive amount on R&D activities in the next period. In the second stage we estimate R&D intensity in the next period, given the supplier started R&D activities.[37] Analogous to Crepon et al. (1998) we assume that firms take up R&D activities if discounted future profits from R&D activities are positive. Let $RD^{*}_{i,t+1}$ be the discounted future profits from R&D of supplier *i* in period *t+1*. We observe that firms invest in R&D in *t+1* if $RD^{*}_{i,t+1}$ is positive. Furthermore we assume the true R&D intensity ($RDINT^{*}_{i,t+1}$) of supplier *i* in period *t+1* is determined by an identical set of explanatory variables with the exception of firm size. Then our estimated model is described by equation (2.3) denoting the selection equation and equation (2.4) denoting the intensity equation.

$$RD^{*}_{i,t+1} \quad = \beta_1 BP_{i,t} + \gamma_1 BUY_{i,t} + \delta_1 SUP_{i,t} + \rho_1 X_{i,t} + \varepsilon_{i,t} \tag{2.3}$$

$$RDINT^{*}_{i,t+1} = \beta_2 BP_{i,t} + \gamma_2 BUY_{i,t} + \delta_2 SUP_{i,t} + \rho_2 Y_{i,t} + \mu_{i,t} \tag{2.4}$$

While *BP* reflects our set of dummy variables capturing buyer power, the vector *BUY* contains the elements *BUYPCM* and *BUYRDINT*, i. e. the intensity of competition and R&D in the buyer industry, respectively. The vector *SUP* contains the elements *NO-COMP*, *COMP* and *DIVERS*. All other variables are captured by a vector of control variables (*X*). The unobserved error term are represented by ε and μ, respectively. Note that vector *X* is identical to vector *Y* with the exception of firm size, since we need to take the exclusion restriction into account. Due to the fact, that $RDINT^{*}_{i,t+1}$ is only observable when $RD^{*}_{i,t+1}$ is positive, we assume joint normality of both disturbance terms $\varepsilon_{i,t}$ and $\mu_{i,t}$.

2.2.5 Results

2.2.5.1 Descriptive statistics

Table 2.6 shows descriptive statistics of the variables of interest differentiated by the supplier's R&D status. The descriptive analysis reveals strong differences between R&D performers and non-R&D performers. The share of R&D performing firms in the

[37] We use the R&D activities in *t+1* to avoid simultaneity problems, which may occur from the fact that R&D investments of a supplier can also have an effect on a supplier's exposure to buyer power as well as a supplier's market environment.

sample is about 46 % with an average R&D intensity of 10,000 DM[38] per employee. The average R&D intensity in the full sample is 4,000 DM per employee.

Table 2.6: Descriptive statistics differentiated by a supplier's R&D status

	Full Sample		R&D performer		Non-R&D performer		T-test	
	Mean	SD	Mean	SD	Mean	SD		
RDINT	0.004	0.013	0.010	0.017				
BP_L[a]	0.330	0.470	0.275	0.447	0.377	0.485	3.482	***
BP_H[a]	0.244	0.430	0.191	0.394	0.289	0.454	3.684	***
BUYPCM[b]	0.638	0.128	0.657	0.131	0.621	0.123	-4.574	***
BUYRDINT[b]	1.891	2.379	2.086	2.425	1.725	2.329	-2.446	**
NOCOMP[a]	0.026	0.159	0.008	0.091	0.041	0.199	3.303	***
COMP[a]	0.580	0.494	0.620	0.486	0.546	0.498	-2.387	**
COMP6+[a]	0.394	0.489	0.372	0.484	0.413	0.493	1.334	
DIVERS	0.285	0.238	0.327	0.235	0.249	0.235	-5.328	***
SIZE	163	376.59	228	484.23	107	237.88	-5.226	***
AGE	18	17.808	19	19.324	18	16.423	-0.481	***
GROUP[a]	0.562	0.496	0.641	0.480	0.495	0.500	-4.771	***
EAST[a]	0.337	0.473	0.313	0.464	0.357	0.480	1.497	
N	1,036		476		560			

[a] Dummy variable. [b] For details on the calculation see Appendix B.1. Columns with heading SD display standard deviations. The last two columns display t-statistics whether a T-test on mean difference between the group of R&D performers and non-R&D performers rejects the Null hypothesis of no difference. The asterisks indicate the corresponding level of significance (* 10 %, ** 5 %, *** 1 %). The variables RDINT, SIZE and AGE are presented in original values. The variable COMP6+ indicates the reference category of 6 or more competitors. Descriptive statistics of the remaining variables are shown in Table B 4 in Appendix B.2.

With respect to our measures of buyer power, we observe significantly lower shares of enterprises being subject to buyer power among the group of R&D performers. For *BP_L* the share among non-R&D performers is about 38 % while in the group of R&D active firms it is only 28 %. The share of firms captured by the stronger measure of buyer power *BP_H* is smaller compared to *BP_L*. The share for *BP_H* among non-R&D performers is 29 % compared to 19 % among the R&D performers. Also, R&D active firms supply to more competitive and technology intensive buyer markets. At the same time, they seem to be exposed to stronger horizontal competition. Their share among firms holding a monopoly is significantly smaller while it is vice versa among the group of oligopolists.

In addition, R&D active suppliers are more diversified in their product range, have more employees, belong more frequently to an enterprise group and are less often located in Eastern Germany.

[38] The unit of currency in the MIP is for historical reasons still Deutsche Mark (DM). 1 DM corresponds to 0.51 Euros.

With respect to industry differences, we observe a significantly higher share of R&D performers in chemicals, machinery, electronics, furniture/toys/sports and IT/telecommunication (see Table B 4 in Appendix B.2). On the contrary, the share of non-R&D performers is higher in wholesale, transportation, media services and consulting/advertising. Regarding the buyers industry, there is a higher share of R&D performers supplying to buyers producing industry intermediaries and capital goods while non-R&D performers make up a higher share among the firms supplying to buyers affiliated to enterprise services.

2.2.5.2 Regression results

Table 2.7 shows the estimated coefficients of the empirical model presented in section 2.2.4.3. For better exposition of the results regarding the different measures of buyer power, columns I and II present the coefficient estimates of the selection equations while estimation results from the intensity equations are reported in columns III and IV, respectively. *BP_i* corresponds to *BP_L* in column I and III and to *BP_H* in column II and IV. Note that the table displays coefficients not marginal effects for the Probit models in columns I and II.

Let us first consider the results of the selection equations which explore the determinants of a supplier's decision to invest in R&D. With respect to our measures of a supplier's exposure to buyer power we find significantly negative coefficient estimates for both *BP_L* and *BP_H*. The magnitude is larger for *BP_H*. The predicted probability to be an R&D performer in the next period is on average 48 % for a supplier which is unaffected by buyer power as defined by *BP_H*. Being exposed to buyer power reduces the likelihood to 35 % which corresponds to a marginal effect of a discrete change, calculated at the means of all other variables, by about 13 percentage points. In case of *BP_L* the drop in probability is 11 percentage points. Hence, a switch from no buyer power to strong buyer power (*BP_H*) reduces the likelihood of a supplier to take up R&D activities by 27 %. This is a substantial reduction and provides strong support for hypothesis 1b. What is more, the results are in line with previous empirical studies.

Table 2.7: Estimation results of generalised Tobit models using different specifications of buyer power

	Selection: $RD_{i,t+1}$				Intensity: RDINT $_{i,t+1}$			
	I		II		III		IV	
	BP_L		BP_H		BP_L		BP_H	
BP_i[a]	-0.269	***	-0.330	***	-0.256		-0.366	**
	(0.100)		(0.107)		(0.170)		(0.186)	
BUYPCM[b]	0.268		0.252		0.907		0.890	
	(0.424)		(0.424)		(0.652)		(0.651)	
BUYRDINT[b]	-0.020		-0.022		0.025		0.023	
	(0.025)		(0.025)		(0.035)		(0.035)	
NOCOMP [a]	-0.730	**	-0.879	***	-0.626		-0.763	
	(0.335)		(0.336)		(0.719)		(0.728)	
COMP [a]	0.050		0.009		0.122		0.082	
	(0.091)		(0.091)		(0.137)		(0.138)	
DIVERS	0.360	*	0.363	*	0.426		0.415	
	(0.196)		(0.196)		(0.317)		(0.318)	
SIZE	0.232	***	0.234	***				
	(0.034)		(0.034)					
AGE	-0.072		-0.071		-0.130		-0.128	
	(0.056)		(0.056)		(0.082)		(0.082)	
GROUP [a]	0.176	*	0.180	*	0.162		0.174	
	(0.094)		(0.094)		(0.162)		(0.163)	
EAST [a]	0.043		0.031		0.139		0.130	
	(0.098)		(0.098)		(0.149)		(0.149)	
Mills Lambda					1.135	***	1.148	***
					(0.389)		(0.385)	
Constant	-2.513	***	-2.472	***	-10.873	***	-10.848	***
	(0.412)		(0.413)		(1.058)		(1.047)	
Industry dummies	yes		yes		yes		yes	
Wald-Test: joint significance of industry dummies	156.36	***	155.81	***	80.24	***	80.84	***
N	1,036		1,036		1,036		1,036	
LR/Wald $\chi 2$	112		111		112		111	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. [b] For details on the calculation see Appendix B.1. Standard errors are shown in parentheses. Standard errors in column III and IV are corrected for the inclusion of the inverse Mills Ratio. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Estimation results of the industry dummies are presented in Table B 5 in Appendix B.2.

In addition, we find that horizontal market structure matters. Being a monopolist reduces the likelihood of being an R&D performer. A switch from a polypolistic market structure to monopoly decreases the probability to be an R&D performer on average by about 30 percentage points ceteris paribus. As we will see in the next section however, this result is not robust to the exclusion of service firms. We find no significant effect of downstream industry characteristics to affect a supplier's R&D decision.

Finally, the supplier's degree of substitutability, the supplier's size and whether the supply firm belongs to an enterprise group increase the probability of being an R&D performer. The latter finding is in line with Cohen and Klepper (1996) who argue that it is beneficial if a firm can spread the fix costs of R&D over larger output. Also the industry affiliation of the supplier does have significant impact on a supplier's likelihood to be an R&D performer (see Table B 5 in Appendix B.2).

Let us now turn to the results of the structural equation estimations, where the R&D intensity is estimated given a supplier engages in R&D (see Table 2.7, columns III and IV). Regarding the measures of buyer power we find a negative but insignificant coefficient of *BP_L* while *BP_H* has a significant negative effect on a supplier's R&D intensity. The implication of this finding is that supplier's with a sales share generated by the largest three buyers of 50 % or more do not exhibit lower R&D intensities compared to suppliers with lower buyer shares. If however, a high sales share is accompanied by easy substitutability or a high number of competitors, the R&D intensity is significantly lower. Being a supplier exposed to strong buyer power decreases R&D intensity on average by 37 %. We again find support for hypothesis 1b stating that buyer power will have a negative effect on suppliers' innovation incentives. As in the selection equation we find no impact of the buyer's industries' characteristics.

Overall both buyer power measures affect the R&D decision of a supplier negatively. As argued before, the effect of *BP_H* is stronger compared to *BP_L*. Thus, we conclude that buyer concentration does have a negative effect on a supplier's R&D incentives. This effect is even stronger if the supplier is facing numerous competitors or sells a product that is easy to substitute.

Our findings constitute an important contribution to the existing literature as we show negative effects of buyer power on suppliers' innovation incentives differentiated by the stages of a supplier's R&D decision for a large sample of firms in various industries. What is more, the estimated negative effects of buyer power are substantial. According to the results from the estimations using *BP_H*, the likelihood of being a R&D performer decreases by 27 % while R&D intensity decreases by 37 %. The magnitude of the effects implies a serious impediment to suppliers' innovation incentives if powerful buyers are present and at the same time the supplied good is substitutable or provided by more than 5 competitors. In addition, our results complement the findings of Farber (1981) and Peters (2000) who find concentration in the buyer industry to have adverse effects on suppliers' R&D spending. Besides, we show that also concentration in the buyer portfolio can be sufficient to generate buyer power.

2.2.5.3 Robustness checks

In order to test whether the results are driven by one particular sector group, we split the sample in manufacturers and service firms and test our model for each of the subsamples again. The sample of manufacturers comprises 660 firm observations while the sample of service firms consists of 376 firms. It turns out that the drop in the number of observations leads to a rejection of the estimated model in the case of service firms. Therefore, we only present the results of the estimations using the manufacturing sample.

Table 2.8: Estimation results of generalised Tobit models for a sample of manufacturing firms using different specifications of buyer power

	Selection: $RD_{i,t+1}$				Intensity: RDINT $_{i,t+1}$			
	I		II		III		IV	
	BP_L		BP_H		BP_L		BP_H	
BP_i[a]	-0.233	*	-0.302	**	-0.184		-0.384	**
	(0.122)		(0.130)		(0.178)		(0.195)	
BUYPCM[b]	1.816	***	1.825	***	1.566	*	1.609	*
	(0.648)		(0.649)		(0.898)		(0.897)	
BUYRDINT[b]	-0.053	*	-0.055	*	0.054		0.052	
	(0.031)		(0.031)		(0.038)		(0.038)	
NOCOMP [a]	-0.690		-0.804	*	-0.516		-0.610	
	(0.443)		(0.440)		(0.801)		(0.805)	
COMP [a]	0.055		0.014		0.121		0.085	
	(0.114)		(0.115)		(0.152)		(0.152)	
DIVERS	0.596	**	0.593	**	0.573	*	0.546	
	(0.245)		(0.245)		(0.348)		(0.348)	
SIZE	0.268	***	0.270	***				
	(0.043)		(0.043)					
AGE	-0.071		-0.071		-0.110		-0.104	
	(0.068)		(0.068)		(0.086)		(0.086)	
GROUP [a]	0.239	**	0.248	**	0.035		0.053	
	(0.118)		(0.118)		(0.183)		(0.184)	
EAST [a]	0.122		0.115		0.238		0.247	
	(0.125)		(0.125)		(0.166)		(0.165)	
Mills Lambda					0.818	**	0.844	**
					(0.397)		(0.392)	
Constant	-2.109	***	-2.092	***	-7.628	***	-7.665	***
	(0.576)		(0.576)		(0.939)		(0.932)	
Industry dummies	yes		yes		yes		yes	
Wald-Test: joint significance of industry dummies	69.92	***	70.25	***	44.52	***	44.83	***
N	660		660		660		660	
LR/Wald $\chi2$	76		77		76		77	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. [b] For details on the calculation see Appendix B.1. Standard errors are shown in parentheses. Standard errors in column III and IV are corrected for the inclusion of the inverse Mills Ratio. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Estimation results of the industry dummies are presented in Table B 6 in Appendix B.

With respect to buyer power, the findings from the full sample are robust to the exclusion of service firms (see Table 2.8, column I for *BP_L* and II for *BP_H*). As expected *BP_H* is larger compared to *BP_L* and the negative effects of buyer power remain substantial. Being exposed to buyer power according to *BP_H* reduces the likelihood of a supplier to invest in R&D by about 12 percentage points. Given that the probability of the average manufacturing firm to invest in R&D is about 60 %, this implies a reduction of almost 20 %.

Regarding downstream industry characteristics we find significant effects upon suppliers' innovation incentives for the sample of manufacturing firms. Downstream competition intensity is now significant and positive concerning the probability of being an R&D performer. The coefficients are roughly equal regardless of the measure of buyer power. For illustrative reasons let us assume that profits in the downstream industry drop by 10 %.[39] Given the estimation results using *BP_H*, this drop in downstream profits increases a supplier's likelihood to invest in R&D by roughly 5 percentage points, which corresponds to an increase of about 8 %.[40] The latter finding is interesting since it shows how closely related supplier's innovation incentives and downstream competition in manufacturing industries apparently are.

Also downstream R&D intensity does now exert a significantly negative effect on a supplier's decision to invest in R&D. As it was the case for downstream competition intensity, the coefficients roughly equal each other regardless of the measure of buyer power. The effect is quite small compared to the other determinants though. An increase in downstream R&D intensity by one percentage point from the subsample mean of 1.4 % to 2.4 %, results in a decrease of the supplier's likelihood to invest in R&D by about 2 percentage points. Note however that an increase of an industries' R&D intensity of a percentage point is highly unlikely.

The strong effect of being a monopolist observed in the full sample is apparently driven by service firms as it is not robust to the sample split. All other effects of the supplier's degree of substitutability, the supplier's size and whether the supply firm belongs to an enterprise group hold also for the subsample.

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[39] For an average firm in our sample this implies that downstream competition intensity increases from 0.675 to 0.743.

[40] This is calculated with all other variables taking mean value.

The results of the intensity equations are also robust to the exclusion of service firms (see Table 2.8 Column III for BP_L and Column IV for BP_H). The marginal effect of being exposed to buyer power according to *BP_H* is now slightly higher, implying a reduction in R&D intensity by 38 %. We also see a weakly significant positive effect of competition intensity on a supplier's R&D intensity.

Summarizing, the results from the robustness check show that results from the full sample are robust to the exclusion of service firms. With respect to the effect of downstream industry characteristics we observe now interesting effects on suppliers' R&D incentives. We find evidence that in manufacturing industries the demand-pull argument applies, i. e. stronger competition leads to higher demand for innovative intermediate goods. This increases not only the likelihood of R&D investments but also the intensity of R&D investment on the supply side. In addition, if the R&D intensity in the buyer's industry is high, suppliers have a lower likelihood to start own R&D activities. This is a reasonable finding if one considers that R&D projects often require a minimum investment. The minimum threshold should be higher if buyers in R&D intensive industries are supplied since they demand highly innovative intermediaries. Given the fact that R&D is mostly financed using cash-flow, the likelihood of own R&D activities decreases as suppliers are not able to bear this cost.

2.2.6 Buyer power and the intensity of competition and R&D in the downstream industry

So far we have analysed the impact of buyer power and downstream industry characteristics on suppliers' innovation incentives separately. This may draw an incomplete picture of the resulting effects on suppliers' innovation incentive because the effects of buyer power and downstream industry characteristics are likely to be intertwined. We will base the discussion of possible interaction effects on the empirical findings for the sample of manufacturing firms.

Let us first consider the case of a powerful buyer facing intense downstream competition. As we have seen in the previous section, downstream competition increases innovation incentives of suppliers. This is due to demand-pull, i. e stronger downstream competition leads to higher demand for innovation. Such innovative inputs allow buyers in very competitive markets to lower the costs of production or distribution, to differentiate away from downstream competitors or to enter new markets. Accordingly, a large buyer will exploit the fact that he accounts for a large share in a supplier's business by steering the R&D of the supplier towards own needs and preferences. In order to make use of the buyer's innovation impulses, R&D investments of the supplier are necessary, since internal R&D investments generate new knowledge on the one hand and create absorptive capacity on the other (Cohen and Levinthal, 1989). The latter allows evaluation and exploitation of externally available knowledge, i. e. the successful integration of knowledge spillovers into the own knowledge stock. This exchange of knowledge will result in the building of co-specialised assets (Teece, 1986). Such a situation obviously increases innovation incentives on the supply side as the supplier's bargaining position relative to the buyer improves and allows a more favourable split of the joint profit. In fact, many studies found buyers to be a main source for technological advance in upstream firms (Klevorick et al., 1995). Also in the presence of a large buyer there is less uncertainty in the sales of new products (Peters, 2000). Against this background we expect a positive effect of strong downstream competition and buyer power on supplier’s R&D incentives.

Let us now turn to the effect of downstream R&D intensity. For manufacturing firms we find a negative effect of high downstream R&D intensity on suppliers’ innovation incentives which can be explained with higher thresholds of minimum investment for R&D projects aiming at buyers in highly R&D intensive industries. Once this threshold is overcome, one should observe higher investments of firms supplying to R&D intensive sectors. This is related to the observation that there is a positive relationship between higher R&D investments carried out in the buyer market and the upstream demand for innovative products (Scherer, 1982b). This is also observed in the results of section 2.2.5.2 and 2.2.5.3 although the coefficients are insignificant. If competition in the downstream market is driven by technology development however, buyers are urged to invest heavily into the development of new products and new process technology. This in turn reduces their profits. As a result these buyers organize R&D within the supply chain more efficiently and along their own business strategy. For instance, car manufacturers have reduced the number of suppliers in order to realize economies of scale (Peters, 2000). In addition, suppliers are highly involved in new product development, receive more technical information and are supported by their buyers more intensively (Becker and Peters, 1997). Even though this should increase innovation incentives of suppliers, car manufacturers could increase their bargaining power due to global sourcing (Peters, 2000). Hence, suppliers may try to save their margin by reducing own effort which should result in a negative relationship between downstream R&D intensity, buyer power and suppliers' innovation incentive.

Table 2.9: Estimation results of generalised Tobit models including interactions between buyer power and downstream industry characteristics

	Selection: $RD_{i,t+1}$				Intensity: $RDINT_{i,t+1}$			
	I		II		III		IV	
	BP_L		BP_H		BP_L		BP_H	
BP_i[a]	-2.303	***	-1.737	**	-1.840		-0.822	
	(0.793)		(0.845)		(1.135)		(1.196)	
BUYPCM[b]	0.701		1.209		0.835		1.146	
	(0.770)		(0.737)		(0.943)		(0.913)	
BUYRDINT[b]	-0.037		-0.043		0.063		0.088	**
	(0.036)		(0.034)		(0.041)		(0.039)	
BUYPCM x BP_i	3.311	***	2.320	*	2.580		1.446	
	(1.231)		(1.305)		(1.677)		(1.760)	
BUYRDINT x BP_i	-0.055		-0.046		-0.041		-0.212	***
	(0.053)		(0.058)		(0.070)		(0.078)	
NOCOMP[a]	-0.745	*	-0.846	*	-0.561		-0.511	
	(0.447)		(0.442)		(0.805)		(0.800)	
COMP[a]	0.043		0.001		0.111		0.100	
	(0.115)		(0.116)		(0.152)		(0.150)	
DIVERS	0.573	**	0.583	**	0.560		0.472	
	(0.246)		(0.245)		(0.346)		(0.342)	
SIZE	0.275	***	0.272	***	-0.117		-0.115	
	(0.044)		(0.043)		(0.086)		(0.085)	
AGE	-0.071		-0.070		0.036		0.063	
	(0.069)		(0.069)		(0.183)		(0.181)	
GROUP[a]	0.249	**	0.255	**	0.237		0.273	*
	(0.118)		(0.118)		(0.166)		(0.162)	
EAST[a]	0.129		0.114		-0.659		-0.746	
	(0.126)		(0.125)		(0.548)		(0.545)	
Mills Lambda					0.816	**	0.765	**
					(0.395)		(0.387)	
Constant	-1.355	**	-1.660	***	-7.092	***	-7.296	***
	(0.640)		(0.626)		(0.917)		(0.908)	
Industry dummies	yes		yes		yes		yes	
Wald-Test: joint significance of industry dummies	72.47	***	72.08	***	44.94	***	44.09	***
Wald-Test: joint significance of RDINT, PCM, BP and their interaction terms	19.61	***	17.38	***	10.39	**	18.03	***
N	660		660		660		660	
LR/Wald $\chi 2$	77		86		77		86	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. [b] For details on the calculation see Appendix B.1. Standard errors are shown in parentheses. Standard errors in column III and IV are corrected for the inclusion of the inverse Mills Ratio. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Estimation results of the industry dummies are presented in Table B 7 in Appendix B.2.

Table 2.9 presents the results of the estimation results for the sample of manufacturing firms. *BP_i* corresponds to *BP_L* in column I and III and to *BP_H* in column II and IV. Note that the table displays coefficients not marginal effects for the Probit models in columns I and II.

We observe that the coefficients of the buyer power variable, the measures of downstream industry characteristics and their respective interactions are jointly significant in all estimations to the 1 % significance level except in the intensity equation employing *BP_L* (see Table 2.9, column III). In the selection equation we find both measures of buyer power and additionally the interactions between buyer power and the downstream competition intensity to be separately significant. Calculating the predicted probabilities with respect to a supplier's exposure to buyer power, we interestingly observe that strong downstream competition is compensating the negative effect of buyer power. Let us first consider the case of a buyer who is active in a highly competitive industry. We take the value representing the 90^{th} percentile in the sample (value equals 0.79) while all other explanatory variables are at their means and predict the probability of a supplier to invest in R&D. For *BP_H* the predicted probabilities of starting R&D do not differ between suppliers being exposed to buyer power and those who are not. That is, there is no difference between firms with respect to buyer power if downstream competition is strong. If we calculate the marginal effect of *BP_L* for the same values, the effect is still negative, i. e. a supplier's probability to invest in R&D decreases by 7 percentage points.

Let us now turn to the case of a buyer who is active in an industry with low competition. We therefore use the value representing the 10^{th} percentile in our sample (value equals 0.53). In case of *BP_H* this corresponds to a drop in the probability of doing R&D of 23 percentage points. The corresponding effect when applying *BP_L* is even higher resulting in a decrease of 26 percentage points.

Note that the marginal effect of buyer power calculated at the means of all other variables (which was reported for the previous estimation results) decreases. Being affected by buyer power according to *BP_H* would result in an 11 percentage points decrease whereas the corresponding effect of *BP_L* is a reduction by 8 percentage points.

Considering the results of the intensity equation we find separate significant effects only in the estimation employing *BP_H*. Here the downstream R&D intensity now has a positive effect while its interaction with *BP_H* is negative. That is, on average a one percentage point increase in downstream R&D intensity results in a 9 % increase of supplier's R&D intensity if the supplier is not confronted with buyer power. If in turn there is buyer power, the effect would be a decrease by 12 %.

Given the findings in this section we conclude that the negative effect of buyer power on a supplier’s R&D probability is robust to the inclusion of interaction terms. In addition, our findings reveal that interactions between buyer power and downstream industry characteristics exist. The negative effect of buyer power on a supplier’s R&D probability is mitigated by downstream competition. This finding is consistent with the argument that large buyers in a highly competitive environment use their influence on a supplier’s business to exchange market knowledge with the supplier. This will result in the building of co-specialised assets and in turn improve the bargaining position of the supplier. Consequently, the supplier has a higher incentive to innovate.

We also find the negative effect of buyer power on a supplier’s R&D intensity still to be present after the inclusion of interaction terms. This effect seems to be closely related to downstream R&D intensity. That is, buyers who invest heavily into R&D but at the same time have bargaining power exert negative effects on suppliers’ innovation incentives.

Note however that our measures of downstream industry characteristics are aggregated on Nace 2-digit level and thus capture competition and R&D intensity comparatively rough. It would thus be an interesting extension of our work to conduct the analysis with more disaggregated data for buyer industries. This could significantly improve our understanding of the interdependencies between buyer power and buyer market conditions on supplier’s innovation incentives.

2.2.7 Concluding remarks

Section 2.2 examines the effects of buyer power on suppliers’ innovation incentives. As theoretical evidence on this relationship is inconclusive, we conduct an empirical study. Existing studies operationalized buyer power either by industry level concentration or relied on subjective assessments of suppliers whether they are exposed to pricing pressure of buyers. This study in contrast uses firm level information on the concentration in the supplier’s sales with respect to the largest three buyers. Compared to existing studies this provides us with a more objective measure of buyer power. Moreover, we exploit information on the number of competitors in the main product market and the substitutability of a supplier’s product in order to capture an even stronger degree of buyer power. Furthermore, our econometric approach enables us to disentangle the effects of buyer power on suppliers' innovation incentives into (i) the effect on a supplier’s decision to start innovation activities and (ii) the effect on the amount of resources spent on innovation.

Against the background of an increasing interest in the effects of buyer power in vertical relationships, our study provides valuable new insights concerning suppliers' innovation incentives. Based on a sample of 1,036 firms across manufacturing and service industries, we find a negative effect of buyer power on a supplier's likelihood to invest in R&D for both measures applied. As one would expect, the effect is more pronounced for the measure indicating strong buyer power. We estimate that a switch from no buyer power to strong buyer power decreases the probability of a supplier to establish R&D activities on average by 27 %. Furthermore strong buyer power also reduces a supplier's R&D intensity. Here a switch from no buyer power to strong buyer power leads on average to a reduction by 37 %.

These effects are robust in sign and magnitude after service firms are excluded from the sample. In addition, using a sample of manufacturing firms revealed that also downstream industry characteristics have an impact on supplier's R&D incentives. We distinguish between downstream competition and downstream R&D intensity which is to the best of our knowledge a novelty in the literature on buyer power and supplier's innovation incentives. We find evidence that in manufacturing industries the demand-pull argument applies. That is, stronger competition leads to higher demand for innovative intermediate goods, thereby increasing not only the likelihood of R&D investments but also the intensity of R&D investment on the supply side. In contrast, we find that suppliers have a lower likelihood to take up R&D activities if downstream R&D intensity is high. This is a reasonable finding considering that R&D projects often require a minimum investment. On one hand, the minimum investment is likely to be higher if buyers are strongly involved in R&D while it on the other hand has to be financed with internal cash-flow. Hence, this implies a lower likelihood of investing in R&D.

Finally, we also explore whether there are joint effects of buyer power and downstream industry characteristics on suppliers' innovation incentives. We interestingly find for the sample of manufacturing firms that the negative effect of buyer power on a supplier's R&D probability is mitigated by downstream competition. This can be explained by spillovers from powerful buyers in a highly competitive environment to their suppliers. Absorbation and exploitation of the spillovers improves the bargaining position of the supplier. Consequently the supplier has a higher incentive to innovate. We also find a negative joint effect of buyer power and downstream R&D intensity on a supplier's R&D intensity. This is in line with the argument that suppliers facing powerful buyers who invest heavily into R&D reduce their efforts in order to maintain their profitability.

From an empirical point of view, section 2.2 provides various links for future research. First, it would be worthwhile to extend the analysis on innovation outputs. That may include the questions whether the presence of powerful buyers affects innovation success and whether such buyers promote particular types of innovation. Second, suppliers which are confronted with buyer power may choose specific ways to appropriate a sufficient share of innovation rents, patenting for instance. Hence, in such circumstances suppliers may exhibit a different patenting behaviour. What is more, longer time series data would be extremely helpful since there may be a significant time lag between buyer power, the decision to invest into R&D, and both the corresponding innovation output as well as the use of protection methods for intellectual property.

3 Market incentives to innovate

3.1 Introduction

Innovation is widely considered to be a key long-term driving force for economic growth.[41] Hence, stimulating business innovation is given a high importance on the political agenda. Government policies can actually take two main routes: they can either directly trigger innovation, for instance by granting subsidies or by public procurement; or they can affect the framework conditions in which firms operate, aiming to make them more favourable to innovation. Among the latter, the intensity and the type of product market competition are major factors. Product market competition in turn results from a complex process involving, among others, technological conditions, trade policy, competition policy per se, and innovation and structural policies in general.

The way product market competition impacts innovation has been studied for a long time. Different arguments and models have been put forward leading to theoretical predictions that range from negative, over positive to curvilinear. Empirical studies so far have been inconclusive either. Comparing these studies to explore the differences in results across countries and industries, it turns out that the empirical studies vary a lot in the use of data, measurement of competition and innovation and econometric approach. This section contributes to the existing research by analysing the nexus between product market competition and innovation at the firm level in Germany. Our study makes use of panel data from 1997-2005 for about 1,015 German manufacturing companies. We compare two measures for product market competition: traditional price-cost margins and the profit elasticity which was recently proposed by Boone (2007) as a better indicator to capture competitive behaviour.

Our econometric approach deviates from most prior research in several aspects. We do not only consider the impact on R&D expenditure but distinguish the effect of product market competition on the decision to invest in R&D and on the amount of R&D given that the firm has decided to conduct R&D. Though this distinction has become popular as the first stage in the model by Crèpon et al (1998) that links innovation and produc-

[41] See e.g the survey by Hall (2010) and the references cited therein.

tivity and has been employed in many cross-sectional studies, to the best of our knowledge, a similar approach to examine the relationship between competition and innovation using longitudinal data is only adopted by Artes (2009) for Spanish firms.

Recent contributions furthermore argue that the effect of competition on R&D also depends on firms' *technological distance* to the frontier as well as on the *technological spread* within an industry (Aghion et al., 2005, Brouwer and van der Wiel, 2010; Alder, 2010). This section contributes to the empirical literature on competition and innovation since our estimation strategy takes account of *both* these factors as well.

We briefly review the existing theory and empirical tests on the relationship between market structure and innovation in the next two sections. Section 3.4 sets out the empirical approach. The results of our estimations are presented in the subsequent section. Concluding remarks are presented in section 3.6.

3.2 Theoretical framework

3.2.1 Competition and innovation

From a theoretical point of view the relation between product market competition on the one hand and innovation on the other hand is not clear-cut. Depending on the assumptions about the type of innovation (e.g. cost-reducing vs. demand enhancing, step-by-step vs. non-step-by-step), the type of market structure before and after the innovation, the strength of patent protection or the dynamics of the innovation process, it is possible to establish negative, positive, u-shaped or inverted u-shaped relations between product market competition and innovation (Gilbert 2006; Schmutzler 2009, 2010; Artes 2009). Traditional theory predicts a negative relationship due to the following three arguments: (i) competition reduces profits and hence internal funds for innovation projects; (ii) competition lowers the rewards from innovation (rent dissipation), and (iii) competition increases the uncertainty about potential reactions of competitors on own innovation activities. Hence, firms with ex ante market power have a higher incentive to innovate. This is called the Schumpeterian effect or Schumpeter hypothesis II (see e. g. Schumpeter, 1942; Dasgupta and Stieglitz, 1980).[42] Arrow (1962) emphasized that competition might encourage innovation. In order to keep their position ahead of established com-

[42] Romer (1990) and Aghion and Howitt (1992) also modelled a negative relation between competition and innovation in their endogenous growth models.

petitors or to avoid market entry of new competitors, incumbents are forced to innovate. This effect of competition on innovation is also called “the escape competition effect”. In two recent papers, Aghion et al. (2001, 2005) argue in favour of an inverse u-shaped relationship. They emphasise that not the amount of post-innovation rents per se incentivize firm to innovate but that it is the likely difference between post-innovation and pre-innovation rents that encourages a firm to invest in innovation. According to their model, innovation activity would rather be low on markets with perfect competition or in a monopoly situation whereas it would be very intense on oligopoly markets. This is due to the two countervailing effects at work: the escape competition effect and the Schumpeterian effect.

Both effects shape a firm’s innovation incentives depending on the level of competition and the technological spread within an industry. If the initial level of product market competition is low, an industry is mostly in a technologically levelled state. This is due to the fact, that the less productive firm – the laggard – has a high incentive to catch up. The benefit of innovation exceeds the profits as laggard. When incumbent firms are operating at similar technological levels (neck-to-neck competing incumbents), it is more likely that the escape competition effect dominates if competition intensifies.[43] The escape competition effect is characterized by a lower reduction in post-innovation rents due to an increase in competition than the reduction in pre-innovation rents. This increase in incremental profits incentivizes firms to foster innovation in order to escape competition. As a consequence, the industry becomes more and more unlevelled with increasing competition, since a laggard’s incentives to catch up diminish because of high costs and lower post-innovation rents. At this stage the Schumpeterian effect is dominating.

As the extent of collusion in a product market is mostly not observable to the researcher, empirical studies in this context frequently interpret increasing competition according to observable measures of competition either on industry level (Aghion et al., 2005; for a recent study applying the profit elasticity see Brouwer and van der Wiel, 2010), firm level or both (e. g. Tingvall and Poldahl, 2006; Artes, 2009; Alder, 2010). Hence, competition is broadly defined and captures for instance entry of new firms, intensifying conduct, a decrease in substitutability, breakdown of cartels and a lot more effects.

[43] The model of Aghion et al. (2005) studies innovation incentives in a duopoly framework. They model an increase of competition as a reduction in the degree of collusion. That is, no competition corresponds to perfect collusion, while perfect competition corresponds to no collusion.

Some studies also instrument the increase of competition by changes in regulation. This is done for instance by Aghion et al. (2005) or Griffith et al. (2006b). Notwithstanding their diversity, empirical measures of competition are successfully applied to test the inverted u-shape relationship between competition and innovation. Accordingly, we formulate the first hypotheses for our empirical part of the paper as:

Hypothesis 1: *The relationship between competition and innovation is inverse u-shaped. That is, for low levels of competition, an increase in competition will lead to higher innovation incentives. Beyond a certain level of competition a further increase of competition will reduce the innovation incentives.*

3.2.2 Technological distance and innovation

The question whether technological conditions within an industry have an impact on a firm's incentives to innovate was firstly raised by Aghion et al. (2005). Their theoretical model assumes a duopoly and postulates a higher incentive to innovate when firms are technologically similar or levelled. An increase in competition then reduces pre-innovation profits which makes technological leadership due to innovation more profitable for the firm. In contrast an increase in competition does not spur innovation incentives if both firms are technologically different, i. e. the sector is unlevelled. The leading firm does not have an incentive to innovate since the difference between pre- and post-innovation profits is the same. The lagging firm faces a decreasing incentive to innovate as with increasing competition the difference between pre- and post-innovation profits declines. It remains unclear, however, what is meant by a levelled sector in case of more than two firms. For instance it is possible that one firm within an industry is operating at the technological frontier while the majority of firms is lagging behind. In contrast to the predictions of Aghion et al. (2005) laggards then may have an incentive to innovate as well since most of their competitors are technologically similar even though they do not operate at the frontier. This leads to the conclusion that it is possible to describe a sector as levelled if the distribution of the firms with respect to their technological distance is narrow. We will therefore formulate our hypotheses according to the distribution of firms' technological proximity.

Hypothesis 2: *Increasing technological differences between firms within an industry, i. e. the sector becomes unlevelled, will lead to lower innovation incentives.*

In a similar vein, Acemoglu et al. (2006) argue that firms, in order to improve their productivity may either imitate or invent production technology to raise their productivity. However, the application of the latter strategy requires high-skilled firms and entrepreneurs which are most efficiently selected under intense competition. Higher competition and a closer position to the technological frontier should foster R&D efforts as the only way to become more productive than competitors is to innovate.

Hypothesis 3: *If competition intensifies, firms operating far away from the technological frontier will reduce their innovation efforts compared to frontier firms.*

Note that the latter hypothesis is often derived from the results of Aghion et al. (2005) when they are adapted to the firm level (see e. g. Tingvall and Poldahl, 2006 or Brouwer and van der Wiel, 2010). Again, this interpretation neglects the distribution of firms' technological proximity as the predictions of Aghion et al. (2005) are derived from a duopoly case.

The presented theoretical evidence mostly assumes that R&D is carried out as soon as incentives are sufficiently high. If the incentives decrease beyond a threshold value, the firm abandons R&D. In reality this is somewhat different, because usually the decision to start R&D activities requires long-term planning and the formation of expectations about the possible return from these activities. In addition, it is costly pausing R&D activities as they have high fixed costs and cannot be adapted on the short-run (Hall, 1992; Sutton, 1998). Given this long-term horizon when R&D activities are taken up, it is likely that e. g. competition does not only affect the innovation incentives of a firm already performing R&D but also the incentives of a non-R&D performing firm. Hence we will explore the impact of competition, technological distance and technological proximity on different stages of the innovation decision. First, we will analyse the decision to start R&D which is followed then by the exploration of the decision how much to invest into R&D.

3.3 Related Literature

Similar to the theoretical work, empirical studies on the relationship between competition and innovation have not been conclusive either. Many studies pointed to a negative relationship between competition and R&D although these results were sensitive to the inclusion of industry effects (see e. g. Levin et al., 1985; Scott, 1984). Blundell et al. (1999) or Geroski (1995) ascertained a positive relationship between product market competition and innovation. Many recent studies found evidence for an inverted u-shaped relationship between product market competition and innovation; e.g. Aghion et al. (2005) for a panel of UK industries, Tingvall and Poldahl (2006) for Swedish firm level data and Brouwer and van der Wiel (2010) for Dutch firms. Nonetheless, it turns out that the results are rather fragile. They are not robust to changes in the innovation measure (R&D intensity instead of citation weighted number of patents; Aghion et al. 2005) or in the competition measure (Tingvall and Poldahl 2006).[44] Similarly, Brouwer and van der Wiel (2010) find support for the inverted u-relationship only in the manufacturing sector but not for services.

Crepon et al. (1998) emphasize the existence of a selection problem since merely a minority of firms is engaged in R&D which is a non-random sample of the firm population. Using a selection model, they find for a sample of French firms monopoly power to have a positive effect on both a firm’s decision to conduct R&D and the decision on the intensity of R&D effort. Artes (2009) took this approach further by testing for a non-linear relationship. Using a panel of Spanish firms, he corroborates a positive effect for the decision to perform R&D. Moreover he provides evidence for an inverted u-relationship between competition and likelihood to start R&D. Yet, when analysing the decision over the extent of R&D activities, he finds monopoly power to have either a negative or no effect at all.

Also Aghion et al. (2009) argue in favour of lower innovation efforts by technologically distant firms. In their empirical model the impact of competition on innovation is different with respect to the technological proximity of firms. A higher threat of entry leads to both higher innovation expenditures and higher productivity growth of already highly efficient incumbents in order to prevent entry. Unlike the technological leaders, firms far away from the technological frontier invest less on innovation when entry threat increases because chances to become the industry’s technological leader are lower compared to the chances of the leader to maintain his position. This holds despite the fact that costs of innovation are the same for all firms. Aghion et al. (2005) provide empirical evidence that an increase in competition leads to higher innovation efforts in sectors with a high share of technologically equal firms when compared to sectors with une-

[44] Correa (2012) finds in the dataset of Aghion et al. (2005) a structural break in the early 1980’s. Taking this break into consideration, the inverted u-shape relationship between competition and innovation does not hold. Instead, he finds a positive relationship for the pre-break period and no relationship at all for the post-break period.

qually distributed firms. This result has been replicated for Sweden by Tingvall and Poldahl (2006). Brouwer and van der Wiel (2010) however do not find support for a steeper inverse U in neck-and-neck sectors for the Netherlands. Acemoglu et al. (2006) find countries with lower competition to slow down significantly more in terms of economic growth when they converge to the technological frontier than countries with intense competition because they fail to switch from the investment (i. e. imitation) to the innovation strategy.[45] Aghion et al. (2009) find incumbent firms to react with higher innovation activity on entry thread of technologically advanced firms in sectors that are initially close to the technological frontier, whereas incumbents in sectors further behind the frontier are found to be discouraged by increased entry thread. Alder (2010) observes that firms being technologically advanced compared to their main competitors are more innovative. For low initial levels of competition an increase in competition is associated with a stronger increase in innovation. The inverted u-shaped relationship between innovation and competition depends however on the measure of innovation. He finds an ambiguous influence of the technological level on the relation between competition and innovation which also seems to depend on the measure of competition.

3.4 Empirical study

3.4.1 Data

For our empirical analysis we employ data from different sources. We derive the profit elasticity from data provided by the German Cost Structure Survey (CSS). Since 1996 the CSS is carried out on annual basis by the Federal Statistical Office and consists of a representative stratified random sample of German manufacturing firms employing at least 20 employees. As the participation in the survey is mandatory, the dataset provides information on roughly 18,000 firms per wave including e. g. sales, employment and several cost structure variables. For the remaining variables we use firm level information from the Mannheim Innovation Panel (MIP) which also consists of a representative stratified random sample of German firms. Data collection is carried out by the Centre for European Economic Research (ZEW) on behalf of the Federal Ministry of Education and Research. The MIP provides annual information on innovative behaviour

[45] Acemoglu et al. (2006) measure competition by the ease of entry. High competition is hence characterized by a low number of procedures to open up a new business.

in the German manufacturing sector since 1992 and is at the same time the German contribution to the European Community Innovation Survey. The target population of the MIP are firms with at least five employees having their headquarters in Germany. Due to reasons of data availability, we restrict the analysis to data from 1997-2005 for the Nace 2-digit industries 15-35. Moreover, we deflated all variables with respective price indices.[46]

We excluded all firms reporting to have no sales or no employees. In order to avoid outlier problems we also drop all observations with an R&D intensity of larger than 2, i. e. a firm's R&D expenditures exceed the sales by 100 %. This is likely to be the case if e. g. start-ups are observed. Additionally, we restrict the PCM to values between 0 and 1 in order to avoid (i) firms making losses which exceed their R&D expenditure and (ii) firms which spend more on R&D than on material and workforce.[47] The latter case is likely to occur if firms spend substantial resources for external R&D. As we are interested in the effect of competition on internal R&D activities since this is typically considered in the theoretical models presented in previous sections, we exclude these firms. The first case is excluded to ensure the comparability between the two measures of competition. We measure competition by the price cost margin (*PCM*) and the profit elasticity (*PE*) as defined by Boone et al. (2007) (see also section 3.4.2.2). As the profit elasticity is estimated in a log-log specification, it is not possible to include firms reporting losses. Therefore, we exclude these firms as well. Finally, we restrict our sample to firms with at least 3 consecutive observations in the panel in order to exploit the variation within the individual firm in our estimations. After cleaning the data we are left with an unbalanced panel of 3,085 observations from 1,015 firms between 1997-2005.

[46] To deflate output figures, we use producer price indices on a 3-digit Nace level for manufacturing. For a few 3-digit Nace classes no indices are published; here, the producer price indices on the corresponding 2-digit Nace level are used as proxy. (In Germany, no producer price indices are published for the classes 17.3,18.3, 20.5, 21.1, 22.3, 23.3, 28.5, 28.6, 29.6, 33.3, 35.3, 35.4, 35.5, 37.1, 37.2.). Investments and physical capital were deflated using the investment goods price index (at a 2-digit level). Material goods were deflated using the price index on intermediate goods (at a 2-digit level). For labour costs we use a weighted index on wage development in labour costs (at a 2-digit level). We furthermore construct an R&D deflator based on the breakdown of R&D expenditure according to R&D investments, expenses for R&D employees and R&D material costs (at a 2-digit level). All indices are elaborated and published by the German Statistical Office (Destatis).

[47] The PCM is defined as sales – material cost – personnel costs + R&D expenditure divided by sales.

3.4.2 Variable specification[48]

3.4.2.1 Innovation activity

A firm's long-term innovation decision is captured by a dummy variable (*RD*) which takes unit value if a positive amount of money is spent on R&D activities in period *t*. The innovative effort (*RDINT*) is measured by a firm's R&D intensity (in log) which is defined as R&D expenditure over employees. This relative measure of innovative effort corrects for size effects and captures the resources spent on R&D activities per employee.

3.4.2.2 Measuring horizontal competition

The most commonly used measures for competition are the *PCM* and concentration measures, e. g. the Herfindahl-Index. Both measures have a long tradition in empirical studies on industrial organization. The use of concentration indices emerged with the structure-conduct-performance paradigm in which the structure of an industry determines the interaction between firms which in turn determines firms' profitability. Highly concentrated industries are perceived to promote higher prices and hence higher margins.[49] The *PCM* captures the extent of the mark up, i. e. the difference between price and marginal cost as percentage of the price. Similar to the concentration ratio, high values of *PCM* are related to low competition because mark ups are high.

Both measures are grounded on theoretical foundations. In the simple Cournot model with homogenous goods, the *PCM* of a firm is determined by the market share and the inverse price elasticity of demand. If the firm level *PCM* is averaged over all firms in the market and weighted with market shares, it represents the Herfindahl-Index (see e. g. Belleflamme and Peitz, 2010). In this case the Herfindahl-Index reflects average profits in the market and provides hence a good indication of market power. In addition, both measures are easily availably or can be computed from readily available data.

However, the theoretical foundations of both measures are possibly shaky.[50] What is more, both types of measures may be misleading when competition increases due to intensified conduct (Boone et al., 2007). The *PCM* is often used as weighted average of firms' *PCM*'s with the weights indicating the firm's market share (see e. g. Nickell,

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[48] For an overview of all applied variable definitions see Table C 5 in Appendix C.4.

[49] For a review of empirical studies in this fashion see Scherer and Ross (1990).

[50] See e. g. Stiglitz (1989) for an example of intensifying competition that leads to higher *PCM*.

1996). Boone et al. (2007) show that an increase of competition caused by intensified conduct leads to a reallocation of market shares between efficient and less efficient firms resulting in a higher weight for the *PCM* of an efficient firm. This may cause the *PCM* to increase, thereby wrongly indicating a decrease in competition. In addition, under constant competitive conditions *PCM* increases when firm's costs decrease. This is rather a sign for efficiency gains or positive supply shocks than an indication of a decrease in competition.

Alternatively, many microeconomic studies draw upon concentration measures to indicate the level of competition (see e. g. Aghion et al., 2003; Blundell et al., 1999; Disney et al., 2003). Concentration is then measured on a more or less detailed industry level. However, these measures are afflicted with an aggregation problem as they reflect the mean of a large number of product markets which is not necessarily indicating the real competitive environment of the firm. All in all, concentration ratios and market shares will be lower in heterogeneous industries comprising a large number of different product markets than in homogenous industries including only a few or merely one product market. Moreover, an increase in competition due to a more aggressive conduct of incumbents leads either to exit or to decreasing market shares for inefficient firms. Ultimately this will result in higher concentration measures, hence wrongly suggesting that competition is decreasing.

Recently Boone et al. (2007) proposed the profit elasticity (*PE*) as an alternative measure for competition. PE is measured on industry level and is defined as the percentage fall in profits due to a percentage increase in costs. They argue that "in a more competitive market, firms are punished more harshly in terms of profits for being inefficient" (Boone et al., 2007; p. 7) implying a higher profit elasticity on markets with a higher intensity of competition. Contrasting the results of *PE* with those of (industry level) *PCM* and Herfindahl-Index they show empirically that changes in conduct are picked up by *PE* while the other measures fail to do so. Yet, applying the *PE* does not solve the aggregation problem which is also of concern for concentration measures since it is measured on industry level. If an industry comprises a large number of product markets, the *PE* may not necessarily indicate the real competitive environment of the firm.

Therefore this paper will employ two measures of competition. First we use the *PCM* as a measure of the competitive pressure on firm-level. It is complemented by the *PE* in order to contrast the results obtained with a firm specific competition measure by an industry level competition indicator.

PCM is measured as difference between sales and costs of both material and employees plus R&D expenditure divided by sales. We add the R&D expenditure in order to make R&D and non-R&D performers comparable. The underlying assumption is that costs of R&D activities, e. g. for personnel or material, are already included in the firm's costs. If we do not add the R&D expenditure this would lead to the situation, that two identical firms which are competing in one product market with otherwise same costs and sales would have different *PCM* values if one is a R&D performer while the other is not. For the ease of interpretation we use absolute values of the *PE* and transform the *PCM* to *1-PCM*. This ensures that we can interpret the coefficient as an increase in competition. *PE* is estimated on Nace 3-digit level and we apply the specification suggested by Boone et al. (2007)[51].

3.4.2.3 The individual distance to the technology frontier

Innovation activities are – apart from competition – further explained by a firm's distance to the technological frontier (*DTF*). Depending on the technological distance firms R&D activities may be either intensified or hampered. Our measure of technological distance is calculated on the basis of the total factor productivity (TFP) and departures from a firm's production function. TFP is defined as residual between the logs of outputs and inputs. This method is well described in the relevant literature (see the overview by Mairesse and Sassenou, 1991).[52] To control for technological distance we have to define the frontier firm. We calculate the TFP on firm level and define the frontier firm to represent the 95th percentile of TFP per industry on Nace 2-digit level and year to avoid outlier problems. Then, we calculate the individual distance to the frontier as the difference in TFP's of the frontier and the individual firm. Finally, dividing the individual distance by the frontier firm's TFP provides a measure of technological distance which is scaled between 0 and 1, indicating a high distance to the technological frontier when it takes values close to 1 and a close distance when it takes values close to 0.

[51] A detailed description of how we estimate the PE is given in Appendix C.1.
[52] A detailed description of how we estimate TFP is given in Appendix C.2.

3.4.2.4 The technological spread within an industry

As mentioned before, Aghion et al. (2005) argue that the effect of competition on innovation depends on the technological proximity of the firms within an industry. However, they measure the technological spread by the mean of the technological distance to the frontier across the firms within the industry. In our view this measure might be imprecise as outliers could pull the mean either upwards or downwards. Hence we would expect the standard deviation of the technological distance within an industry to be a more precise measure of the technological spread. Therefore, we additionally construct a variable indicating the standard deviation of the technological distance within a Nace 2-digit industry per year (*SDDTF*) to capture the technological spread.

3.4.2.5 Other control variables

Finally, we include several control variables in our empirical model to account for other factors that may influence innovation activities. Innovation may also be affected by the availability of resources. As a result we control for liability of size or smallness by adding the firm's workforce (full time employees) in logs (*SIZE*). Moreover, we control for the capital intensity (*CAP*) which reflects barriers to entry of competitors. It is calculated as tangible assets divided by the number of employees (in logs).[53] High entry barriers may allow appropriating the returns of innovation to a larger extent compared to a situation with low entry barriers. Hence they can be considered as an important signal for the long term profitability of innovation activities. Therefore we assume that barriers to entry have an effect on the long term decision to engage in R&D activities but not on the short term intensity decision.

All mentioned control variables are lagged by one period to alleviate potential simultaneity problems. Furthermore we add a control variable whether a firm is part of an enterprise group (*GP*) as this may allow spreading fixed costs of R&D over larger output, thereby facilitating the decision to invest in R&D (Cohen and Klepper, 1996). We also control for the fact whether an enterprise is located in East Germany (*EAST*) to control

[53] Note that MIP does not provide information on the firms' capital stock for the years 1999 and 2000. Hence, we interpolated the missing values by using the mean of the capital intensity (in logs) in the firm's Nace 2-digit industry per year.

for regional differences. Finally, we include both industry dummies (*IND*) and time dummies (*YEAR*).[54]

3.4.3 Estimation strategy

We employ a modified version of the model by Griffith et al. (2006b) which was originally proposed and estimated at the industry level. It relates a firm's innovation effort to the prevailing intensity of competition and the firm's distance to the technological frontier. It also analyses possible interactions between competition intensity and technological distance. Adapting the approach to the firm level requires taking account of a possible selection problem since only the R&D intensity of R&D performers is observable. This may lead to inconsistent estimation results, especially in the context of panel data as the selection may be related to the error term of the individual effect. Consequently, we perform a test for sample selection bias as proposed by Wooldridge (2010, p. 833f.).[55] As the test rejects sample selection for both of our competition measures, we therefore continue to estimate the decision to start R&D and the decision of how much to invest as separate models.

As mentioned before, we will use lagged variables in order to alleviate endogeneity problems occurring from the fact that innovation activity may affect competition. In order to model a firm's R&D investment decision, we assume that RD_{it}^* represents a latent variable of firm i in period t which can be interpreted as a threshold value, e. g. the expected present value of revenues due to a firm's R&D activities in period t. The latent variable RD_{it}^* is determined by a vector of explanatory variables from the previous period ($X_{i,t-1}$) and an error term (u_{it}). As a firm's threshold value is unobservable to us, we furthermore assume that we observe firm i to invests in R&D if RD_{it}^* is positive, i. e. $RD_{it} = 1$ if $RD_{it}^* > 0$ and zero otherwise. Consequently, we estimate in the first step the following equation:

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[54] Our reference industry is Food/Tobacco (Nace 2 15-16) while the reference year is 1998. The breakdown of industry dummies and the according Nace 2-digit industries can be found in Table C 6 in Appendix C.4.

[55] The test is on the Null hypothesis that $E(v_{it}|\, X_i, s_i, u_i) = 0$ which rules out partial correlation of the idiosyncratic error term v_{it} with the selection indicator s_i. To this end, we first estimate a Probit model as given in (3.1). We derive the inverse Mills ratio and use it as regressor in a fixed effects model similar to the equation in (3.2). Since the coefficient is insignificant, we cannot reject the Null hypothesis that idiosyncratic errors are strictly exogenous on the selection indicator. For a detailed description of the test on sample selection see Wooldridge (2010, p. 833ff.)

$$RD_{it}^{*} = X_{i,t-1}{}'\beta + u_{it} \qquad (3.1)$$

The true R&D intensity is then determined by the following intensity equation:

$$RDINT_{it}^{*} = X_{i,t-1}{}'\gamma + \varepsilon_{it} \qquad (3.2)$$

Moreover, $RDINT_{it}^{*}$ is determined by the same vector $X_{i,t-1}$ which explains also equation (3.1), i.e. the decision to invest into R&D or not. Our choice of explanatory variables to be included in X has been explained in the previous section.

RD_{it} is a binary variable, so we estimate equation (3.1) using a Probit model. Moreover we allow for random individual effects. Then the error term is defined as $u_{it} = u_i + v_{it}$ with $v_{it} \sim N(0, \sigma_v^2)$. The random individual effects require us to assume that all explanatory variables are uncorrelated with the individual effect. To relax this assumption we apply a procedure suggested by Mundlak (1978) and Zabel (1992) and define a time constant individual effect to be $u_i = \bar{X}'\delta + \xi_i$ with $\bar{X}$ being a vector including the individual means of the explanatory variables and $\xi_i \sim N\left(0, \sigma_\xi^2\right)$. We now assume a conditional normal distribution of the individual effect, i. e. $u_i | X_i \sim N\left(\bar{X}'\delta, \sigma_\xi^2\right)$.[56] Hence, the the individual effect and the explanatory variables are now allowed to be correlated. Equation (3.1) changes to:

$$RD_{it}^{*} = X'\beta + \bar{X}'\delta + \xi_i + v_{it} \qquad (3.3)$$

Analogously we include a random individual effect in the intensity equation. We define the error term to be $\varepsilon_{it} = \varepsilon_i + \tau_{it}$ with $\tau_{it} \sim N(0, \sigma_\tau^2)$. Then the time constant individual effect is defined as $\varepsilon_i = \bar{X}'\varphi + \mu_i$ with $\bar{X}$ including the same individual means as above and $\mu_i \sim N\left(0, \sigma_\mu^2\right)$. Equation (3.2) changes to:

$$RDINT_{it}^{*} = X'\gamma + \bar{X}'\varphi + \mu_i + \tau_{it} \qquad (3.4)$$

Note that our specification allows for a separate analysis of (i) the effects of the time invariant level of competition via the individual effect and (ii) the effects due to an increase of competition beyond the average level. For a better exposition of our results, we will interpret the impact of $\bar{X}$ as “constant” effect while the effects from X are re-

[56] A similar approach is taken by Heckman and MaCurdy (1980) who model life cycle labor supply behavior and define the individual effect to be a function of time constant variables and mean values of time varying variables.

ferred to as “deviation” effect as they represent effects occurring due to the deviation of the mean.

Our approach might be prone to endogeneity issues as the innovative effort of the firms may reversely influence the competition intensity. We tackle this problem by employing a specification using lagged values of competition as instrument. One can argue that the competition intensity in *t-1* affects a firm’s R&D expenditure in *t* but that in turn the R&D expenditure in *t* will not affect the competition intensity in *t-1*. Hence the inclusion of lagged values of competition intensity will alleviate the problem of simultaneity. Furthermore, we could use longer lags in order to instrument competition. This would reduce the number of observations in our sample considerably, hence we refrain from using longer lags. In addition, to avoid endogeneity we may profit from our short panel. The majority of firms in our sample are observed for 3 consecutive periods.[57] It is very unlikely, that R&D investments undertaken within this period have an impact on competition intensity, the distance to the technological frontier, the technological spread within an industry or the firm size. The study of Mansfield et al. (1971) shows, that there is a considerable time lag between investment in R&D and returns from it. Ravenscraft and Scherer show that the mean time lag is between 4 and 6 years. Taking into account that we use lagged variables to explain observed R&D behaviour, we conclude that endogeneity issues are unlikely to occur.

3.5 Results

3.5.1 Descriptive Statistics

Table 3.1 shows the overall descriptive statistics of our sample with respect to R&D activity. 63 % of the observations conduct R&D activities with a mean R&D intensity of about 4550 DM per employee.[58] T-tests show that for each explanatory variable descripted, the observations from the group of R&D performers differs significantly from the group of non-R&D performers.

Regarding the technological distance we observe for the group of non-R&D performers a higher mean of *DTF* and a higher mean of *SDDTF*. Therefore, non-R&D performers

[57] We observe roughly 44 % of the panel firms for 3 consecutive years.

[58] For historical reasons the unit of currency in the MIP is Deutsche Mark (DM). 1 DM equals roughly 0.51 EURO.

in our sample are further away from the technological frontier and operate in industries with a larger technology spread when compared to their R&D performing counterparts.

Moreover our data shows that non-R&D performers are on average significantly smaller, less capital intensive and less often part of a company group. Firms in East and West Germany do not differ regarding their R&D activities.

Table 3.1: Descriptive statistics differentiated by firms' R&D status

	Full Sample		R&D performer		Non-R&D performer		T-test	
	Mean	SD	Mean	SD	Mean	SD		
RD^a	0.633	0.482	1	0				
RDINT (ln)			-5.393	1.394				
1-PCM $_{t-1}$	0.703	0.155	0.691	0.155	0.724	0.153	5.79	***
PE $_{t-1}$	2.497	0.778	2.548	0.756	2.409	0.807	-4.78	***
DTF $_{t-1}$	0.579	0.241	0.542	0.240	0.641	0.229	11.21	***
SDDTF $_{t-1}$	0.244	0.023	0.242	0.022	0.247	0.025	5.08	***
SIZE (ln) $_{t-1}$	4.519	1.537	4.910	1.508	3.843	1.339	-19.71	***
CAP (ln) $_{t-1}$	-2.928	1.075	-2.876	1.013	-3.019	1.171	-3.57	***
GP_t^a	0.398	0.490	0.464	0.499	0.285	0.451	-9.94	***
$EAST_t^a$	0.374	0.484	0.373	0.484	0.377	0.485	0.20	
N	3,085		1,954		1,131			

[a] Dummy variable. Columns with heading SD display standard deviations. The last two columns display t-statistics whether a T-test on mean difference between the group of R&D performers and non-R&D performers rejects the Null hypothesis of no difference. The asterisks indicate the corresponding level of significance (* 10 %, ** 5 %, *** 1 %). Descriptive statistics of the remaining variables are presented in Table C 7 in Appendix C.4.

Regarding the competition variables our data show an overall mean of *1-PCM* of 0.70 which indicates a moderate level of competition. This corresponds to average operating profits (*PCM*) of 30 % of the sales for the full sample.[59] Non-R&D performers exhibit a slightly lower share of operating profits (28%) compared to the sample of R&D performers (31%). This indicates a slightly lower level of competition for the sample of R&D performers compared to the sample of non-R&D performers. Interestingly, this observation is reversed when we consider *PE*. Here we find a higher level of competition for the sample of R&D performers when compared to the sample of non-R&D performers. This result is likely driven by the fact that *PE* is measured on industry-level while *1-PCM* is measured in firm-level. The overall sample mean of the absolute values of profit elasticity is 2.5 which corresponds to a reduction of profits by 2.5 % if variable costs increase by a percentage point.

[59] Note that the true profit may be significantly smaller as the PCM is calculated net of capital cost.

The minimum value of profit elasticity is measured in 2002 and 2003 for the manufacturers of coke, refined petroleum products and nuclear fuel. Here a percentage increase in variable costs resulted in a profit reduction of 0 %. In contrast the maximum value is measured for manufacturers of wood and wood products in 1999 where a percentage cost increase resulted in roughly 5 % lower profits.

Table 3.2: Descriptive statistics of the measures of competition

Competition measure		Mean	Std. Dev.	Min	Max	Observations[a]	
1-PCM	overall	0.70	0.15	0.01	1	N =	3,085
	between		0.14	0.03	0.98	n =	1,015
	within		0.08	0.23	1.14	T =	3.04
PE	overall	2.50	0.78	0	4.91	N =	3,085
	between		0.74	0	4.80	n =	1,015
	within		0.34	1	3.72	T =	3.04

[a] N in this column denotes the number of total observations, n denotes the number of firms and T represents the average number of observations per firm.

Table 3.2 provides further descriptive statistics with respect to our measures of competition. We see that total variance in both variables is largely due to the variance between firms whereas variance within firms is considerably lower. For both measures the within standard deviation is about half of the between standard variation. This implies that the effects of a change in competition will be largely identified through the variation between the firms, as the variation within is fairly low. This is especially the case for the PE which is not surprising as it is a measure on industry level.

3.5.2 Regression results

For the sake of exposition we will report results of estimations employing the *1-PCM* only. This is due to the fact that the results for the competition measure on firm level are stronger than for *PE* which measures competition on industry level. The main results from the estimations applying *PE* are presented in Appendix C.3 in Table C 1 and Table C 3 and will be discussed jointly with the results from *1-PCM*.

Table 3.3 reports the results of the different specifications used for the estimation of the Random Effects Probit on a firm's decision to invest in R&D. Recall that the individual effect is characterized by group means. We interpret the mean value as "constant" effect while we refer to the single value as "deviation" effect because it represents effects occurring due to the deviation of the mean.

The results for the test on an inverse u-shaped relationship between competition and innovation incentives are reported in column I of Table 3.3. It turns out that we find no evidence of an inverted u-shape relationship between the level of competition and the decision to invest into R&D for German manufacturing firms. Thus we do not find evidence for hypothesis 1. Consequently, we test for a linear effect (see Table 3.3, column II). Again we do not find a significant effect for the deviation effect. There is however a strongly significant constant effect of competition on the probability to engage in R&D, which is reflected by the mean of *1-PCM.* It is strongly significant across all specifications. Holding all else equal, this implies that high average levels of competition are related to a lower likelihood of investing in R&D. Therefore, our result supports the argument of Schumpeter (1942) who argues that competition reduces profits which are in turn required to finance innovation projects internally. If the average level of competition is high, expected returns on R&D investment will be lower. Hence, the likelihood of doing R&D decreases. For *PE* we find no effect of competition on the probability to invest in R&D (see Table C 1 in Appendix C.3).

Another significant determinant of the likelihood to invest in R&D is the technological distance to frontier. Here both effects –constant and deviation – are strongly significant but show contrary signs. That is, the mean of *DTF* does negatively affect the likelihood to invest in R&D holding all else equal, while the estimated coefficient for the effect of an increase beyond the mean level is positive. This is found to be a fairly robust observation, as it also appears in all the estimation using the *PE* (see Table C 1 in Appendix C.3). Therefore, we conclude that a rise in *DTF* above the mean level on average increases the likelihood to perform R&D, all else equal. This is likely in order to catch up and close the technological gap to rivals. If the average *DTF* is too large however, on average the likelihood to perform R&D reduces, since the present value of future revenues from R&D activities decreases.

We find that the technological spread within an industry affects the R&D decision of a firm negatively as expected, but the deviation from the mean as well as the constant effect of *SDDTF* are insignificant. For the estimations using the *PE* the effect of the constant technology spread within an industry is weakly significant though. This suggests that a high constant level of differences in productivity between firms in an industry, on average decreases the incentives to do R&D, all else equal. Hence, our results provide in part support for hypothesis 2.

Table 3.3: Estimation results of the Random Effects Probit using *1-PCM*

	Dependent variable: RD_{it}							
	I		II		III		IV	
1-PCM $_{t-1}$	1.152		-0.190		0.631		0.253	
	(1.077)		(0.211)		(0.507)		(2.221)	
1-PCM $_{t-1}$ x 1-PCM $_{t-1}$	-1.048							
	(0.834)							
DTF $_{t-1}$	0.650	**	0.666	**	1.632	***	0.664	**
	(0.301)		(0.302)		(0.613)		(0.305)	
SDDTF $_{t-1}$	-1.026		-0.974		-1.081		0.329	
	(1.050)		(1.045)		(1.046)		(6.613)	
1-PCM $_{t-1}$ x DTF $_{t-1}$					-1.385	*		
					(0.749)			
1-PCM $_{t-1}$ x SDDTF $_{t-1}$							-1.81	
							(9.029)	
CAP (ln) $_{t-1}$	0.000		0.001		-0.001		0.001	
	(0.043)		(0.043)		(0.043)		(0.043)	
$GP^{a}{}_{t}$	-0.087		-0.086		-0.087		-0.086	
	(0.089)		(0.089)		(0.089)		(0.089)	
$\overline{1-PCM}$	-1.388	***	-1.367	***	-1.390	***	-1.365	***
	(0.395)		(0.396)		(0.402)		(0.397)	
$\overline{DTF}$	-0.835	**	-0.823	**	-0.849	**	-0.820	**
	(0.394)		(0.395)		(0.394)		(0.397)	
$\overline{SDDTF}$	-3.381		-3.600		-3.350		-3.576	
	(2.800)		(2.787)		(2.801)		(2.795)	
$\overline{SIZE}$	0.390	***	0.394	***	0.390	***	0.394	***
	(0.038)		(0.038)		(0.038)		(0.038)	
$\overline{CAP}$	0.063		0.063		0.061		0.063	
	(0.060)		(0.060)		(0.060)		(0.061)	
$\overline{EAST}$	0.310	***	0.304	***	0.309	***	0.305	***
	(0.090)		(0.090)		(0.090)		(0.090)	
Constant	-0.185		0.202		-0.369		-0.127	
	(0.824)		(0.764)		(0.813)		(1.854)	
Wald-Test: joint significance of 1-PCM, DTF/SDDTF and interaction terms	$\chi2$ (2) = 1.68				$\chi2$ (3) = 8.25	**	$\chi2$ (3) = 1.82	
N	3,085		3,085		3,085		3,085	
Wald Chi	361		362		363		362	
Log likelihood	-1,542		-1,543		-1,541		-1,543	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. Robust and clustered standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Estimation includes 7 time dummies and 9 mean industry variables. Results of the remaining variables are presented in Table C 8 in Appendix C.4.

The results of the estimation testing for an interaction effect between *DTF* and *1-PCM* are presented in column III of Table 3.3. We find a negative interaction effect which is weakly significant. The Wald-Test on joint significance rejects the Null hypothesis of *DTF*, *1-PCM* and their interaction to be jointly zero to the 5 % significance level. Thus, we find support for hypothesis 3 which states that if competition increases, firms operating far away from the frontier will have less innovative incentives compared to frontier firms. Note, that this result is also found for the *PE* (see Table C 1 in Appendix C.3).

Column IV of Table 3.3 shows the results of the estimation testing for an interaction effect between the technological spread and competition. The interaction effect between *1-PCM* and *SDDTF* is negative, but insignificant. Also a Wald-Test on joint significance of *PCM* and *SDDTF* cannot reject the Null hypothesis of all coefficients being jointly zero. This is also observed applying *PE* as measure of competition.

Regardless of competition measure we find the mean values of firm size, location in East Germany and industry affiliation to be influential determinants of a firm's likelihood to do R&D.

Let us now turn to the results of the correlated Random Effects OLS estimations in Table 3.4, where we estimate the level of *RDINT* for the sample of R&D performers. We do not account for a possible selection bias in our estimation, as we test for it but could not find evidence for it.[60] Again, the results of the non-linear specification are presented in column I. Column II provides the estimation results for a linear specification while columns III and IV report coefficient estimates for specifications including interactions of *1-PCM* with technological distance and the technological spread, respectively.

By and large, the results confirm our findings from the correlated Random Effect Probit. We cannot find evidence for an inverted u-shape relationship between competition and R&D intensity in the data, as expected in hypothesis 1. The mean of *1-PCM* does again have a strong and significant negative impact on a firm's R&D intensity, while the deviation effect is insignificant (see Table 3.4, columns I and II). To find merely a significant effect of the mean value of *1-PCM*, is not much of a surprise, considering the fact that the within variance of the competition variables is relatively small (see Table 3.2). Consequently, the mean explains already a considerable share of within variation.

[60] The test on selection bias proceeds as suggested by Wooldridge (2010, p. 833f.). For further details see section 3.4.3., fn. 55)

Table 3.4: Estimation results of the Random Effects OLS using *1-PCM*

	Dependent variable: $RDINT_{it}$							
	I		II		III		IV	
1-PCM $_{t-1}$	-0.751		0.370		1.988	***	1.908	
	(1.210)		(0.241)		(0.544)		(2.230)	
1-PCM $_{t-1}$ x 1-PCM $_{t-1}$	0.903							
	(0.942)							
DTF $_{t-1}$	-0.761	**	-0.753	**	1.205	*	-0.770	**
	(0.311)		(0.310)		(0.635)		(0.310)	
SDDTF $_{t-1}$	-0.319		-0.355		-0.546		4.183	
	(1.226)		(1.236)		(1.269)		(6.781)	
1-PCM $_{t-1}$ x DTF $_{t-1}$					-2.890	***		
					(0.837)			
1-PCM $_{t-1}$ x SDDTF $_{t-1}$							-6.306	
							(9.118)	
CAP (ln) $_{t-1}$	0.034		0.033		0.031		0.034	
	(0.040)		(0.040)		(0.040)		(0.040)	
$GP^a{}_t$	0.087		0.088		0.087		0.089	
	(0.092)		(0.092)		(0.092)		(0.092)	
$\overline{1-PCM}$	-2.467	***	-2.499	***	-2.548	***	-2.492	***
	(0.451)		(0.446)		(0.442)		(0.445)	
$\overline{DTF}$	-0.289		-0.310		-0.338		-0.294	
	(0.403)		(0.403)		(0.397)		(0.402)	
$\overline{SDDTF}$	5.162	*	5.412	*	5.363	*	5.502	*
	(3.037)		(3.047)		(3.064)		(3.045)	
$\overline{SIZE}$	-0.056		-0.060		-0.057		-0.060	
	(0.041)		(0.042)		(0.041)		(0.042)	
$\overline{CAP}$	-0.035		-0.034		-0.027		-0.032	
	(0.060)		(0.060)		(0.059)		(0.060)	
$\overline{EAST}$	0.312	***	0.315	***	0.315	***	0.315	***
	(0.092)		(0.092)		(0.092)		(0.092)	
Constant	-5.099	***	-5.420	***	-6.369	***	-6.551	***
	(0.925)		(0.849)		(0.910)		(1.936)	
Wald-Test: joint significance of 1-PCM, DTF, SDDTF and interaction terms	F(2,705) = 1.68				F(3,705) = 5.95	***	F(3,705) = 0.99	
N	1,945		1,945		1,945		1,945	
R^2	0.31		0.31		0.32		0.31	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. Robust and clustered standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively Estimation includes 7 time dummies and 9 mean industry variables. Results of the remaining variables are presented in Table C 9 in Appendix C.4.

We find that an increase of *DTF* beyond the individual mean reduces on average the R&D intensity significantly, all else equal. The individual average of the *DTF* does not affect *RDINT* significantly. Recall that we find the likelihood of doing R&D to be negatively affected by the individual mean of the *DTF*, while upward deviations from the mean slightly increase the probability to invest in R&D.

This finding highlights the fact, that the R&D investment decision is likely to have a long-term perspective, while the decision upon the amount of R&D expenditure is affected by short-term deviations of the *DTF* from its individual mean. If the technological distance is too large, the expected returns of R&D may be too small to justify an R&D investment in general. Once the R&D investment is carried out, then rather short-term changes in technological distance affect firms' innovation incentives.

The estimations using *PE* confirm our results for *1-PCM*. In addition, there is also a weakly significant negative effect of the mean individual level of DTF on R&D intensity (see Table C 3 in Appendix C.3).

We observe a weakly significant and positive coefficient of the mean of the technology spread within an industry (*SDDTF*) across all specifications. That is, if a sector is highly unlevelled in terms of productivity, firms have a higher incentive to invest in R&D given they are already R&D performer. The innovation incentives of R&D performers in unlevelled sectors are larger because the presumably larger productivity gaps in unlevelled sectors allow for higher returns on R&D compared to levelled sectors with similarly productive firms. We also observe this to be the case in the estimations applying the *PE* (see Table C 3 in Appendix C.3).

A look at the interaction term in column III shows that the effects of *1-PCM* and *DTF* on *RDINT* are closely intertwined. We find evidence for a negative and significant interaction effect between 1-*PCM* and *DTF*. While an increase in *DTF* provides positive innovation incentives to firms under low competition, the effect turns negative if the level of competition increases. This is in line with the argument, that the incremental profit of innovating is higher than the cost of R&D at low levels of competition (Aghion et al.; 2005) and supports hypothesis 3. As the level of competition increases, the incremental profit in relation to the cost of R&D decreases. We do not find this effect however for the *PE* (see Table C 3 in Appendix C.3).

Our estimation results provide no evidence for a joint effect of the technological spread within an industry and the level of competition regardless of the measure of competition. Besides, we find that firms located in East Germany have a significant larger R&D intensity than firms located in West Germany. This can be explained by the substantial amount of subsidies that was provided to firms in East Germany in order to smooth the transformation process from a centrally planned economy towards a market economy.

To summarize, our results do not provide evidence of an inverse u-shaped relationship between competition and R&D incentives as proposed by Aghion et al. (2005). Using data from German manufacturing firms we are not able to reproduce the findings of Aghion et al. (2005) for the UK, of Tingvall and Poldahl (2006) for Sweden and

Brouwer and van der Wiel (2010) for The Netherlands who all found an inverted u-shape between competition and innovation.

It rather seems that there is a linear negative relationship between the level of competition and R&D incentives for manufacturing firms in Germany. Our findings support the traditional argument of Schumpeter (1942) that competition reduces profits and ultimately internal funds for innovation projects. As R&D is often financed with operating profits, the negative effect of the *1-PCM* ‘s mean value is highly plausible and in line with the empirical findings of e. g. Crepon et al. (1998) and Artes (2009). Crepon et al. (1998) find monopoly power to positively affect the R&D decision of a firm using French data. However Crepon et al. (1998) use an average market share of the firm to proxy the degree of competition intensity which is rather an indicator of market structure. Artes (2009) uses firm level profit margins and also different measures of market structure and competition, e. g. the concentration ratio, and the number of competitors to explain the start of R&D activities and the intensity decision.

We do find weak support for hypothesis 2 which states that increasing technological disparity between firms in a sector results in diminishing innovation incentives when applying the *PE*. Our results show interestingly, that this is only valid for the R&D decision. Given a firm in a highly unlevelled sector decides to perform R&D we find a higher R&D intensity of firms in unlevelled sectors. This finding can be explained by the strong productivity advantage of R&D performers in unlevelled industries. The technological disparity provides strong incentives to increase R&D as future returns are likely to be higher compared to a situation in which the majority of rivalling firms is equally productive.

Furthermore, our results support the view that not only the degree of technological proximity within an industry matters for innovation incentives, but also the individual distance to the frontier firm. Hypothesis 3 states that if competition intensifies, firms operating far away from the technological frontier will reduce their innovation efforts compared to frontier firms. This is found for both stages of the innovation decision. We find strongly significant effects for both the individual constant level of *DTF* as well as the deviation from the individual mean. This also holds in the estimations employing the *PE*.

Furthermore our results highlight how sensitive an analysis of the relationship between competition and innovation incentives is to the applied measures of competition. Using the firm level measure *1-PCM*, we find robust results while for the industry level measure *PE* we basically find results for the first stage only, i.e. the decision whether or not to invest in R&D. The observed difference in the quality of the results may well be due to measurement issues. Firstly, *1-PCM* is measured on firm level while *PE* is an aggregation of different product markets on Nace 3 level. Hence *1-PCM* should pick up changes in profits of a firm more accurately than an average measure of profit elasticity over an industry. This is even more so as the measurement of *PE* does not allow for the inclusion of firms making losses. Hence, the elasticity for the aggregate of several product markets is likely to be underestimated.

3.6 Concluding remarks

In this chapter we analyse the interplay between competition, technological distance and innovation. Against the background of existing theoretical and empirical literature we expect (i) to find an inverted u-relationship between innovation and competition, (ii) firms in technologically very uneven sectors to invest less in innovation and (iii) frontier firms to invest more in R&D than technologically distant firms if competition increases.

Major challenges when investigating the relationship between competition and innovation are on one hand the appropriate definition and measurement of competition and a solution for the problem of reverse causality between innovation and competition measures on the other hand. In this chapter we use a widespread measure of competition intensity – the firm level *PCM* – and complement it with a recently proposed measure of industries' profit elasticity (Boone et al., 2007) which is argued to capture the intensity of industry competition better than industry level *PCM* or concentration indices. What is more, the problem of reverse causality is attenuated by the use of lagged variables capturing competition intensity.

Using data of German manufacturing firms, we apply a two-step approach in order to estimate the impact of competition intensity and technological distance on a) a firm's R&D decision and b) a firm's decision on R&D intensity. We choose this procedure to include the non-R&D performers which are usually excluded from empirical studies on innovation and competition.

We find that competition and technological distance play an important role for a firm's R&D incentives. However, the results do not support a u-shaped relationship between competition and innovation. Instead, we find a high constant level of competition to negatively affect innovation incentives which supports Schumpeter's (1942) argument that intense competition reduces margins thereby reducing opportunities for financing innovation projects.

We find weak evidence for firms in technologically unlevelled sectors having a lower probability of performing R&D which is in line with hypothesis 2. This is not the whole story however. The results of the random effects OLS estimates show that a high constant level of technological disparity is linked to higher R&D intensities. This can be explained by stronger R&D incentives for R&D performers in unlevelled sectors due to larger productivity differences between the firms within an unlevelled sector compared to rather equally productive firms in a levelled sector. The large productivity gap translates into higher margins for R&D performers. Therefore, expected profits of R&D in an unlevelled sector are higher compared to a levelled sector given the R&D investment is sunk.

A firm's distance to the technological frontier does have a pronounced effect on innovation incentives. We observe that a constantly high level of technological distance implies a lower probability to engage in R&D activities which is countervailed by a positive effect of a short term increase in the technological distance. In contrast, the constant level of technological distance seems to be less important for the decision on the intensity of R&D. This finding highlights the different perspectives of both decisions. The investment decision will have a long-term perspective. Therefore, the constant effect of technological distance is highly relevant. In opposite to that the decision on the R&D intensity is rather a short-term decision. According to our results R&D spending decreases if a firm's technological distance grows in the short-term.

Moreover, the results show that both technological distance and competition are strongly related to each other and that an effect of competition on innovation incentives should not be considered separately from technological distance. Our findings support the argument of Aghion et al. (2005) that technological laggards will be stronger negatively affected by an increase in competition than frontier firms which is consistent with hypothesis 3.

Our empirical findings for German manufacturers provide important implications for policy makers. Firstly, the results suggest that changes in competition policy aiming at an increase of competition in a market would lower innovation incentives if in response to the policy intervention the constant level of competition increases. Therefore, the introduction of policy measures aiming at an increase in innovation and R&D spending by stimulating competition as postulated in the Horizon 2020 strategy could have negative effects on innovation incentives of German manufacturers. Second, an increase in competition beyond the average level, e. g. by entry, and its impact on firms' innovation incentives will depend on the individual distance to the technological frontier. If the distance is too large, more competition will affect innovation incentives negatively. Therefore, careful assessment is needed when policies concerned with the stimulation of competition are applied to industries with a small fraction of highly productive firms. While the very productive firms are likely to respond positively in terms of R&D engagement on intensifying competition, the less productive firms may either refrain from starting R&D or reduce their spending.

4 Selective search, sectoral patterns and the impact on product innovation performance

4.1 Introduction[61]

Research has frequently shown that firm success in technology-driven industries critically depends on the ability to invent and commercialize innovative technology embodied in new products (e.g., Katila, 2002; Katila and Ahuja, 2002). In this respect, firms with the ability to create new technological knowledge have been praised for generating knowledge internally and combining it with external knowledge sources (Rosenkopf and Nerkar, 2001). However, the process of identifying knowledge to be integrated into the organization's own knowledge base requires that firms deliberately search for and reach out to promising knowledge sources. Search has been characterized as the fundamental mechanism enabling firms to learn, evolve and refocus the organizational knowledge base. This goes beyond "local search", which assumes that research and development (R&D) activities are connected to the firm's previous R&D (Nelson and Winter, 1982). The literature has emphasized the importance for firms of moving beyond local search and reconfiguring the existing knowledge base (Kogut and Zander, 1992; Teece et al., 1997). In fact, the type of knowledge search and the defining direction and priority of boundary-spanning search activities have been found to substantially impact innovation performance (Katila, 2002; Katila and Ahuja, 2002; Laursen and Salter, 2006).

In this chapter, we shed new light on the relationship between the type of knowledge search of a firm and its innovation performance. We propose that innovation management requires a more nuanced understanding of the nature and effects of knowledge search to implement them successfully. Prior research has largely focused on the dimensions of overall breadth and depth (e.g. Laursen and Salter, 2006). We argue that the description of knowledge search along its breadth and depth underestimates the degree of heterogeneity among the various knowledge sources they encompass. Instead, we

[61] Chapter 4 has been published as Köhler, C., W. Sofka and C. Grimpe (2012). "Selective search, sectoral patterns, and the impact on product innovation performance." *Research Policy* **41** (8): 1344-1356.

suggest that the choice of a type of knowledge search is a selective process. Management will choose certain directions for the firms' knowledge search that target particular knowledge sources (e.g., product market, science, suppliers).

Based on this conceptualization of selectivity in the knowledge sources that firms target through their particular search, we focus on the implications for a firm's success with new product introductions, thereby leaving out potential effects on other types of innovation like process or organizational innovations. In this respect, we suggest that these targeted types of knowledge search differ with regard to whether they generate new-to-market innovations or imitations, i.e. new-to-firm only. Imitated product innovations are distinctively different from new-to-market innovations in their degree of novelty. Imitations refer to existing products, services or processes that are adapted by the focal firm, for example through observing or reverse-engineering competitors' innovations. They could be refined to reinforce their ability to create value for the firm (Ettlie, 1983) or to improve and exploit existing technological trajectories (Gatignon et al., 2004). Contrary to imitations, new-to-market innovations are novel in the sense that they initially do not have a directly competing innovation. Distinguishing between both types of innovation output is important for at least two reasons. First, many studies on innovation focus on patents as output measures that reflect new-to-market innovations because the patent office requires a certain "innovative step" in the novelty of an innovation for it to qualify for a patent application. Nevertheless, a significant amount of business R&D is directed towards imitations. Second, the role of search for external knowledge may be substantially different depending on the type of innovation output the firm seeks to achieve.

Moreover, existing research has mostly focused on the manufacturing sector and, more specifically, on high-technology industries. Identifying how firms learn and how their knowledge evolves, though, should not be limited to manufacturing industries, particularly given the increasing importance of service sectors for most modern economies. Therefore, we adopt a novel typology of sectoral patterns of innovation developed by Castellacci (2008, 2010), which provides an integrated view of innovation characteristics in both manufacturing and services industries. The idea of a sectoral taxonomy is based on Pavitt's (1984) seminal contribution to highlight major features of the innovation processes and the distinct trajectories followed by industrial sectors. It is therefore fitting to integrate the role of search into particular sectoral patterns of innovation. Both the distinction between imitation and new-to-market innovation output and the sectoral pattern of innovation have been largely neglected in the extant discussion of knowledge search (e.g. Katila and Ahuja, 2002; Laursen and Salter, 2006; Rosenkopf and Nerkar, 2001), which is why they warrant further investigation.

While we derive hypotheses for the effects of particular types of knowledge search on the two types of innovation output, we choose an exploratory approach, i.e. no ex-ante hypotheses, for differences of these effects within certain sectoral patterns of innovation. Our empirical study is based on a comprehensive dataset of 4,933 manufacturing and service firms from five Western European countries. The data include measures on commercialized innovations, which can be considered superior to patents, an intermediary innovation output and typically only relevant in certain industries (Griliches, 1990). Moreover, the sample from five European countries provides close to representative information on manufacturing and service firms in major Western European economies.

The next section details our theoretical framework to develop our hypotheses. Section 4.3 describes our empirical methods. Results are presented in the subsequent section. Section 4.5 provides concluding remarks.

4.2 Theoretical framework

4.2.1 The role of search for innovation performance

It is widely accepted that a firm's ability to innovate is tied to the pool of knowledge available within the organization (e.g., Subramaniam and Venkatraman, 2001). The generation of new knowledge has traditionally been connected to a firm's in-house research and development (R&D) activities. Recent literature, however, points to the advantages of combining internal investments with external resources (e.g. Cassiman and Veugelers, 2006) to benefit from complementarities. In other words, firms have begun to open up their innovation processes to external knowledge. This trend of so-called "Open Innovation" allows firms to access and exploit external knowledge while internal resources are focused on core activities (Chesbrough, 2003). Both supply and demand oriented aspects put firms in a position to acquire knowledge externally. On the one hand, there is an increasing availability of external knowledge, e.g. from universities, customers and specialized suppliers (e.g., von Hippel, 1988; Link and Scott, 2005; Perkmann and Walsh, 2007; van Echtelt et al., 2008). On the other hand, firms are pushed to find new sources for external innovation impulses because of increasing competitive pressures, shorter product life cycles as well as technological opportunities beyond their traditional fields of expertise (e.g., Calantone et al., 1997; Chatterji, 1996; Kleinschmidt and Cooper, 1988; Ojah and Monplaisir, 2003). Several studies have identified positive performance effects of incorporating external knowledge (e.g. Gemünden et al., 1992; Laursen and Salter, 2006; Love and Roper, 2004).

A crucial element in the open innovation activities of firms is a firm's search for external knowledge. A firm's external knowledge search encompasses an "organization's problem-solving activities that involve the creation and recombination of technological ideas" (Katila and Ahuja, 2002, p. 1184). Consequently, investments in problem-solving activities should result in favourable combinations and linkages of users, suppliers and other relevant actors in the innovation system. Laursen and Salter (2006) discuss the concepts of breadth and depth as important factors in a firm's search. Leiponen and Helfat (2011) complement this view by extending the concept of breadth to innovation objectives. They find that the breadth of knowledge sources and of innovation objectives positively influences innovation success at the firm level. Although a broader set of external sources and innovation objectives reduces the risk of unexpected developments, it has to be taken into account that a firm is constrained in terms of the capacity to absorb external knowledge (Cohen and Levinthal, 1989, 1990). These limitations include the level of overall attention a firm's management can dedicate to these activities (Ocasio, 1997). A proper search for external knowledge should therefore concentrate on certain external sources as a vast number of information sources would hamper selection and in-depth exploration processes (Koput, 1997). Contrary to search breadth, search depth can be described as the extent to which firms draw deeply from various external sources for innovation impulses (Laursen and Salter, 2006). Both breadth and depth depict a firm's openness to external innovation impulses (Chesbrough, 2003). Studying the UK manufacturing sector, Laursen and Salter (2006) find that the relationship between search breadth and depth and innovation performance has an inverted u-shape. This means that while search efforts initially increase a firm's performance, there is a trade-off from "over-searching" the environment. At a certain threshold it requires too much management attention (Ocasio, 1997) and has a negative effect on innovation performance.

In a similar vein, Katila and Ahuja (2002) focus on search depth and search scope in the search and problem-solving activities of firms in the robotics industry. Contrary to Laursen and Salter (2006), they define search depth as the extent to which a firm reuses existing internal knowledge, while search scope indicates how widely a firm explores externally available knowledge. The latter largely corresponds to search breadth as defined by Laursen and Salter (2006). However, Katila and Ahuja's (2002) definition of search depth puts greater emphasis on exploiting the established knowledge base within the firm. Consistent with the results of Laursen and Salter (2006), Katila and Ahuja (2002) observe an inverted u-shaped relationship between the search effort and innovation performance, which again points to the negative consequences of too extensive search activities. They also present evidence that the interaction of search breadth and depth is positively related to innovation performance because it increases the uniqueness of resource recombinations: A deep understanding of firm-specific knowledge assets that is extended towards a new application (scope) creates unique and more valuable combinations of resources.

4.2.2 Selection of knowledge sources

The conceptualization of a firm's knowledge search along the dimensions of its breadth and depth implies that the targeted knowledge is largely homogeneous with regard to its source. Following Laursen and Salter (2006), a firm focusing, for example, solely on lead customer knowledge may be assumed to conduct a knowledge search that is as broad and deep as a firm that concentrates its search for knowledge completely on universities. This assumption may be correct once the external knowledge has entered the firm and is already assimilated with existing knowledge stocks. However, we expect the homogeneity assumption of the knowledge of any firm's knowledge search to fail as long as the knowledge remains unidentified outside the firm's boundaries. This "scanning" stage is crucial for the successful implementation of external knowledge sourcing (Doz et al., 2001). Todorova and Durisin (2007) point out that the transformation of external knowledge is one of the most important steps for absorbing it. This reflects the fact that external knowledge can be assumed to be highly heterogeneous in nature.[62]

We argue that management will define a firm's search for external knowledge based on its source. Put simply, we propose that management choice is not between breadth and depth; rather it provides certain directions for the firm's own research efforts. These

[62] Typical categorizations of heterogeneity in knowledge include distinguishing between tacit and formal (e.g., Cowan et al., 2000; Dyer and Hatch, 2004; Polanyi, 1967), specific and generic (e.g., Breschi et al., 2000), and embodied and disembodied (Romer, 1990), and whether it consists of information or know-how (Kogut and Zander, 1992).

directions should reflect the potential value of a knowledge source and how easily it can be accessed and transferred. Focus is thus not so much on the recipient firm's absorptive capacity but rather on the value of the knowledge source. The ultimate, economic value for the searching firm is ex-ante not clear. The value is significantly lower if the sourced knowledge is technologically premature, reflects myopic perspectives or is also readily available to competitors (Frosch, 1996; Katila and Chen, 2008; Mansfield, 1986). Hence, the ultimate value assessment of an external knowledge source depends on whether the knowledge will lead to a successful invention, whether this invention will generate economic returns and whether these returns can be appropriated by the firm making the investment in the first place. The perception of these factors can be expected to influence the selection of a particular type of knowledge search (March and Shapira, 1987). In the following, we will discuss major differences between the knowledge sources of the product market, science, and suppliers.

The product market side has received considerable attention particularly in the marketing literature as part of the "market orientation" of firms (for a review see Kohli and Jaworski, 1990). This broader conceptualization emphasizes a shift in corporate culture towards creating superior value for customers (e.g. Slater and Narver, 2000). Customers and competitors can be considered the primary elements of a product market driven knowledge search. Both groups are necessarily too important to be neglected as their actions have an immediate impact on a firm's sales. Impulses from both groups have been found to propel innovation success. Customers significantly contribute to product innovations even with a high degree of novelty (Lukas and Ferrell, 2000). Moreover, they are especially valuable as knowledge sources when their specific demands are anticipatory for larger market segments in the future (von Hippel, 1988; Beise-Zee, 2001). However, identifying these leading customers has been found to be challenging. Customer knowledge is oftentimes tacit, unarticulated and focused on the customer's own myopic needs (Frosch, 1996; von Zedtwitz and Gassmann, 2002). Literature has therefore cautioned managers not to focus reactively on customers' immediate needs. It is necessary to balance this narrow "consumer-led" approach with proactive measures for identifying long-term latent customer needs (Ketchen et al., 2007; Slater and Narver, 1998, 1999).

Competitor knowledge is different with regard to its accessibility. Competitors operate in a similar market and technology context (Dussauge et al., 2000). Their knowledge is oftentimes embodied in the products or services available on the market. That makes it easier to identify relevant aspects and absorb them. However, it limits the opportunities for generating economic returns because of the reduced degree of novelty. In this respect, a market-oriented knowledge search is more likely associated with imitations or "me-too" products (Lukas and Ferrell, 2000). Knowledge accessed through such a search can be rather familiar and without a high degree of novelty. As a result, our first hypothesis reads:

Hypothesis 1: *Market-driven search is stronger associated with imitation success than with new-to-market innovation success.*

Science-driven search requires a different set of specialized competencies. Universities are the primary producers of fundamentally new knowledge and technology. The knowledge produced often has a high degree of novelty, which provides important business opportunities (e.g. Cohen et al., 2002). What is more, academic incentive systems for knowledge publication and sharing make university knowledge largely a public good (Perkmann and Walsh, 2007). However, university knowledge is frequently further removed from commercial application and requires substantial investments in development to commercialize it (Link et al., 2007; Siegel et al., 2004). Moreover, firms require specialized absorptive capacities to assess and transfer this type of knowledge. Assessing the full value of the often tacit and causally ambiguous knowledge may only be possible through joint research activities in which university and firm scientists develop a mutual understanding and language in practice over time (Laursen and Salter, 2006). Science-driven knowledge search should therefore be shaped by the competencies in the firm's own R&D department (Asmussen et al., 2009). The skills as well as the personal networks of firm scientists and engineers developed through education and training (Adler and Kwon, 2002) are a necessary prerequisite.

A firm's search based on knowledge from universities or public research institutes can thus be assumed to provide highly novel knowledge and corresponding opportunities for commercialization (e.g. Cohen et al., 2002). Hence, university knowledge has the potential to lead to the generation of new-to-market innovations.

Hypothesis 2: *Science-driven search is stronger associated with innovation success of new-to-market innovations than with imitation success.*

Finally, suppliers have been characterized as an important driver for innovation success (e.g. Pavitt, 1984). On the one hand, firms may use suppliers to learn faster, accelerate the product development process and rely on resources created in a co-evolutionary relationship between the focal firm and its network of suppliers (Dyer and Hatch, 2004; van Echtelt et al., 2008). On the other hand, knowledge produced by suppliers is not necessarily unique since potential competitors may equally benefit from the supplier's expertise. Moreover, Kotabe (1990) finds that firms that rely heavily on supplier knowledge may lose relevant manufacturing process knowledge, which may cost the firm the opportunity to improve their manufacturing technology in a rapidly changing technological environment. As a result, the effects of supplier-driven knowledge search can be expected to affect imitation and new-to-market innovation equally.

Hypothesis 3: *Supplier-driven knowledge search is equally associated with success of new-to-market innovations as well as imitations.*

4.2.3 Search and sectoral patterns of innovation

Existing research on knowledge search that distinguishes between the manufacturing and the service sector is scarce. Most empirical analyses are either explicitly limited to firms in manufacturing (e.g. Laursen and Salter, 2006) or rely on patent statistics to trace knowledge flows (e.g. Katila and Ahuja, 2002). The latter approach is implicitly focused on manufacturing firms as several studies show that firms in manufacturing sectors are significantly more likely to patent than service firms (e.g. Arundel and Kabla, 1998; Harabi, 1995). Although a fairly rich body of literature on innovation in services has developed in recent years (for a recent review see Paswan et al., 2009), it has been argued that many studies actually lack relation to the well-established models for the study of innovation in manufacturing industries (Gallouj and Weinstein, 1997). Castellacci (2008, 2010) therefore calls for a more integrated view of the patterns that innovation activity takes in both manufacturing and services sectors. Our research responds to this call and explores, based on the sectoral taxonomy developed by Castellacci (2008), the importance of the different types of knowledge search for achieving either imitation or new-to-market innovation performance. Due to the novelty of the adopted taxonomy we will, however, not derive any ex-ante hypotheses on expected relationships within each of the sectoral patterns presented.

The sectoral taxonomy suggested by Castellacci (2008) identifies four main sectoral groups, which are defined along two dimensions: (1) their function in the economic system as a provider and/or recipient of advanced products, services and knowledge; and (2) their sectoral technological trajectory, which characterizes innovation activities. The technological trajectory can be seen as a pattern of "normal" problem solving activity

(Dosi, 1982). The pattern is sectoral to the extent that industries differ significantly in their ability to exploit the dominant natural trajectories (Nelson and Winter, 1977). This implies that those sectors whose knowledge base is closely related to emerging technology fields enjoy higher growth prospects as they exhibit higher dynamism and technological opportunities. The well-known taxonomy developed by Pavitt (1984), which groups firms into four major patterns of innovation, builds on the idea that those patterns can be characterized by different technological trajectories. The supplier-dominated, scale-intensive, specialized suppliers, and science-based industries, as defined by Pavitt, however, focus on the manufacturing sector, thus neglecting the emergence of advanced services which are closely related to new technological trajectories. Examples include new services in the information and communications sectors which have opened up the way for future growth opportunities (Castellacci, 2008).

Instead of proposing, however, a new taxonomy of service industries to complement those used to characterize manufacturing industries (e.g., Miozzo and Soete, 2001), Castellacci (2008) puts emphasis on the interdependence and vertical linkages that bind together different groups of manufacturing and service sectors. Based on the two dimensions outlined above (vertical chains and technological content), he distinguishes between advanced knowledge providers (AKP), supporting infrastructural services (SIS), producers of mass production goods (MPG), and producers of personal goods and services (PGS). Both AKP and SIS are characterized as providing rather intermediate goods and services to other sectors while MPG and PGS assume a higher position in the vertical chain by providing rather final goods and services. In contrast to this, both AKP and MPG are characterized by a higher technological content than SIS and PGS, i.e. the former are able to develop new technologies internally to provide them to other sectors.[63]

The role of search for achieving innovation performance within these four categories can consequently be expected to differ according to the sector's position in the vertical chain and the technological content. Market-driven knowledge search has been described as being conducive to accessing customer and competitor knowledge that, due to the lack of novelty, will lead to imitation rather than new-to-market innovation suc-

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[63] Castellacci (2008) moreover identifies two sub-groups per category: knowledge-intensive business services and specialized suppliers manufacturing (AKP), science-based manufacturing and scale-intensive manufacturing (MPG), network infrastructure services and physical infrastructure services (SIS), supplier-dominated goods and supplier-dominated services (PGS). For ease of interpretation, these sub-groups will however be omitted from the following analysis.

cess. As MPG and PGS are classified as providing rather final goods and services to the market, closeness to customers and competitors is likely to be important. Market-driven knowledge search might therefore convey highly relevant knowledge for firms in these categories to achieve success with their innovations. However, due to the lack of novelty, it is likely to be the firm's ability to generate imitations that will benefit from this type of knowledge search.

Science-driven knowledge search, by contrast, can be assumed to provide highly novel knowledge and corresponding opportunities for commercialization. They should hence be more valuable to firms characterized by higher technological content like AKP and MPG. As a result, it is likely that those firms' innovation performance with market novelties will increase compared to those with imitations. Finally, supplier-driven knowledge search has been described as theoretically inconclusive with respect to the type of innovation performance it is likely to foster. On the one hand, knowledge from suppliers can be immediately relevant and even evolve in a co-evolutionary way together with the focal firm's knowledge and hence provide a head start over competitors. On the other hand, such knowledge can in principle also be accessed by competitors if they collaborate with the same supplier, leading to less novelty in the innovation outcome. Consequently, the role that supplier-driven search will play within the four sectoral patterns is unclear and requires ex-post analysis.

4.3 Empirical study

4.3.1 Data

The empirical part of our study is based on cross-sectional data from the third Community Innovation Survey (CIS-3), which was conducted in 2001 under the co-ordination of Eurostat. The survey covers the innovation activities of enterprises in the EU member states (including some neighbouring states) during a three-year period from 1998-2000. What is exceptional about CIS-3 is that it offers representative firm data from all EU member states, which are to a great extent relevant to the questions raised in our study.

The micro data of CIS-3 also provide information on the two-digit industry code (NACE) of a firm. This means that it is possible to assign firms to different sectoral patterns of innovation. As the data are anonymized, it is impossible to identify single firms or to trace the exact answers back to the respective firms (Eurostat, 2005). The dataset we use in this study offers data for five Western European member states, which make up a sample of 4,933 observations of enterprises from the following countries: Belgium (636 firms), Germany (1,446 firms), Greece (332 firms), Portugal (489 firms) and Spain (2,030 firms). Sectoral patterns were identified based on the firms' NACE 2-digit classification (Castellacci, 2008). Table 4.1 provides details on the industries represented in our analysis.

Table 4.1: Industry breakdown

Industry	NACE Code (Rev. 1.1)	Sectoral pattern
Manufacturing		
Food and tobacco	15 – 16	Personal goods and services
Textiles, clothing and leather	17 – 19	Personal goods and services
Wood / paper / publishing / printing	20 – 22	Personal goods and services
Chemicals (incl. pharmaceuticals)	24	Mass production goods
Plastics / rubber	25	Mass production goods
Glass / ceramics	26	Mass production goods
Metals	27 – 28	Mass production goods
Machinery and equipment	29	Advanced knowledge providers
Office and computing machinery	30	Mass production goods
Electrical machinery and apparatus	31	Mass production goods
Radio, TV and communication equipment	32	Mass production goods
Medical, precision and optical equipment	33	Advanced knowledge providers
Motor vehicles and trailers	34	Mass production goods
Transport equipment	35	Mass production goods
Manufacturing n.e.c. (e.g. furniture, sports equipment and toys)	36 – 37	Personal goods and services
Services		
Wholesale trade and commission trade	51	Supporting infrastructure services
Transport and storage (land, water, air)	60 – 63	Supporting infrastructure services
Post and Telecommunications	64	Supporting infrastructure services
Financial intermediation	65 – 67	Supporting infrastructure services
Computer, engineering and R&D services	72, 73, 74	Advanced knowledge providers

A major benefit of CIS-3 is that it provides direct, importance-weighted measures for a comprehensive set of variables for a firm's innovation management (Criscuolo et al., 2005). General managers, heads of R&D departments or innovation management are asked directly if and how they are able to generate innovations. Such immediate information on processes and outputs can be added to traditional measures for innovation such as patents (Kaiser, 2002; Laursen and Salter, 2006). That seems to be especially relevant for our research question as service firms have a lower propensity to patent their innovations.

Innovation surveys like CIS rely on firms' self-reporting. This might raise quality issues regarding administration, non-response and response accuracy (for a discussion see Criscuolo et al., 2005). However, the implementation of the survey is designed to limit possible negative effects. The fact that the survey is conducted via mail prevents certain shortcomings and biases of telephone interviews (for a discussion see Bertrand and Mullainathan, 2001). Moreover, the survey is accompanied by extensive pre-testing and piloting in various countries, industries and firms with regard to interpretability, reliability and validity (Laursen and Salter, 2006). In order to improve response accuracy, the questionnaire offers detailed definitions and examples.

4.3.2 Variables and method

4.3.2.1 Measuring success of new-to-market innovations and imitations

Several authors have introduced different concepts for measuring innovation success (for an overview see Hagedoorn and Cloodt, 2003). One possibility is to use innovation inputs (R&D expenditures) as an indicator of innovation efforts and (indirectly) innovation success. Another way is to look at the outcome of innovative efforts, such as patents, new processes, services and/or products. The latter is the perspective that we choose for our study. Furthermore, we distinguish between new-to-market innovations and imitations by considering the degree of novelty. We refer to a product or service as a new-to-market innovation if it is new not just to the firm but also to its overall market. In contrast, we consider a product or service to be an imitation if it is new to the firm but has alternatives on the market.

The success of an innovation largely depends on market acceptance. For this reason we define innovation success as the share of sales achieved with products/services new to the market on the one hand and the share of sales achieved with products/services new to the firm on the other.[64] For ease of presentation we will subsequently limit the terminology for innovation outputs to the terms "market novelties" for products and/or services new to the market and "firm novelties" for products and/or services new to the

[64] Not all of a firm's "new to the market" products are necessarily "new to the world"; they may be new to the firm's specific market only.

firm only. There is no implicit or explicit distinction between innovative products and services beyond the industry classification.

4.3.2.2 Capturing knowledge search

Measuring knowledge spillovers is a challenging task since they leave no paper trail. Several studies use patent statistics and subsequent citations to capture them (e.g., Galunic and Rodan, 1998; Rosenkopf and Nerkar, 2001). However, such an approach is not always appropriate as “not all inventions are patentable, not all inventions are patented” (Griliches, 1990, p. 1669). Moreover, the distribution of patenting firms is often heavily skewed. This is for example demonstrated by Bloom and van Reenen (2002). In their study, 72% of the sample of almost 60,000 patents by UK firms originates from just twelve companies. Patenting implies the disclosure and codification of knowledge in exchange for protection (Gallini, 2002). The majority of valuable knowledge may therefore never be patented. Moreover, patent statistics provide limited opportunities to identify distinct types of knowledge search because they do not offer any information on the relationships between the two firms identified in the patents (e.g. whether they are customers or competitors). Therefore, we use survey questions to gain information about external knowledge sources. Importance-weighted answers indicate the value of their contribution. More precisely, respondents are asked to evaluate the importance of the main sources for their innovation activities on a 4-point Likert scale ranging from “not used” to “high”. We use information about seven different sources: suppliers, customers, competitors, universities, public research institutes, professional exchanges (e.g. conferences), as well as exhibitions and fairs. In a similar setting, Laursen and Salter (2006) generate indices for the breadth and depth of a firm’s knowledge search based on these questions. Breadth is measured as the number of different sources used while depth is measured as the number of highly important sources. We deviate from their approach in order to identify a firm’s targeted knowledge search.

We argue that R&D managers develop targeted types of knowledge search with a certain direction. This is in contrast to Laursen and Salter (2006), who assume that knowledge search is defined on the basis of breadth and depth and thus ignore direction. We inspect the correlations between the several knowledge sources as shown in Table 4.2 and find that customers and competitors, universities and public research institutes, and suppliers, professional exchanges and exhibitions/fairs are correlated with each other. This observation provides grounds for the assumption that firms apply targeted knowledge searches (Sofka and Grimpe, 2010). We therefore apply a principal component factor analysis in order to identify underlying factors. The data appear to be suitable (Cronbach's alpha scale reliability coefficient: 0.70; Kaiser-Meyer-Olkin measure of sampling adequacy: 0.69). We identify three factors with an eigenvalue greater than one. We conduct an orthogonal varimax rotation in order to interpret the factors with respect to their informational content. The orthogonality assumption of the factors is tested through a likelihood ratio test, which confirms the independence of all factors with an error probability far below one percent (Kaiser and Rice, 1974). Factor loadings identify three individual factors distinctively (above 0.69), as illustrated in Table 4.3.

Table 4.2: Correlation matrix of knowledge sources

	Supplier	Customer	Competitor	University	Public Research Institute	Professional Exchange	Exhibitions and Fairs
Supplier	1						
Customer	0.118	1					
Competitor	0.166	0.441	1				
University	0.132	0.208	0.175	1			
Public Research Institute	0.130	0.171	0.144	0.571	1		
Professional Exchange	0.224	0.207	0.265	0.352	0.289	1	
Exhibitions and Fairs	0.266	0.264	0.309	0.203	0.203	0.547	1
N	4,933						

The retained factors reflect our conceptualization of knowledge search defined along specific search directions instead of rather broadly defined breadth and depth. The first factor is characterized by scientific contributions to innovation processes (public research institutes and universities). Therefore we will refer to this factor as "science-driven knowledge search". Suppliers, professional exchanges, and exhibitions/fairs load highly positive on the second factor. This is surprising at first sight as our theoretical argumentation is largely based on supplier interaction without taking into account professional exchanges or fairs in particular. Then again, supplier knowledge provides the highest level of uniqueness and Kaiser-Meyer-Olkin measure (KMO) of any item in the factor analysis. This indicates that supplier knowledge is the defining influence behind factor 2. We suspect that fairs and professional exchanges serve as the contact points at which firms find and connect with potential suppliers and are therefore considered an element of search for this particular factor. Hence, we interpret this factor as "supplier-driven knowledge search". Nevertheless, it should be kept in mind that it does not exclusively capture supplier knowledge but a broader conceptualization in which knowledge is made "accessible" (fairs, exhibitions, exchanges) or can be procured. In contrast, the third factor reflects a considerable contribution to innovation processes coming from the firms' market environment (customers and competitors). We interpret this factor accordingly as "market-driven knowledge search". We will use the three derived factor scales as focus variables to test our hypotheses empirically.

Table 4.3: Results of the principal component factor analysis

	Factor 1	Factor 2	Factor 3	Uniqueness	KMO[a]
Supplier		0.703		0.505	0.851
Customer			0.845	0.264	0.707
Competitor			0.807	0.301	0.720
University	0.865			0.224	0.647
Public Research Institute	0.869			0.232	0.654
Professional Exchange		0.698		0.369	0.712
Exhibitions and Fairs		0.762		0.331	0.695
Overall					0.695

[a] Kaiser-Meyer-Olkin measure of sampling adequacy. Presented factor loadings are yielded after varimax rotation. Factor loadings below 0.5 are excluded from the table.

4.3.2.3 Control variables

We include several control variables in our empirical model to account for other factors that may influence the estimation results. Obviously, the success of a firm's innovation activities depends crucially on the level of its investments in research and development. These in-house R&D investments have been found to form a firm's absorptive capacity for identifying, assimilating and exploiting external knowledge (Cohen and Levinthal, 1989, 1990). Hence, we include R&D intensity measured by R&D expenditures as a share of sales. Furthermore, valuable knowledge is often the result of accumulated R&D over time, which typically requires a dedicated R&D department. We include a dummy control variable for whether the company performs R&D continuously. As a firm's innovation success may be affected by the availability of resources we control for a liability of size or smallness by adding the firm's sales from the start of the reporting period (1998) in logs. A firm's degree of internationalization is captured by the export intensity which is measured as ratio of exports to total sales. As our observations stem from various European countries, it is necessary to control for effects of the national regulation environment as well as peculiarities of the innovation system. This is done by incorporating country dummy variables into the regression. If a firm is part of a group, it can spread certain functions among subsidiaries or draw from their resources. We therefore add a dummy variable to control for this fact. In addition, some firms may only invest in process innovation. The innovation success of these activities cannot be accounted for. We thus add a dummy variable for process innovators.

4.3.3 Estimation strategy

In order to test the three hypotheses, we estimate two separate empirical models for both dependent variables: share of sales with firm novelties and share of sales with market novelties. As the dependent variables in all models are shares, they are censored between 0 and 1 with a significant fraction of observations having a value of zero. We address this issue by estimating Tobit models. For the exploratory part of our analysis we run the same estimations on subsamples representing the four sectoral patterns. The size of the overall sample allows for a sector-specific split with each subsample containing at least 800 observations. An alternative approach could have been to generate interaction terms between the type of knowledge search and the sectoral patterns. However, due to potential multicollinearity and difficulties in interpretation of multiplicative interactions in non-linear models, we opt for separate estimations (e.g. Salomon and Jin, 2010).

We benefit from a comprehensive dataset that does not limit the empirical findings to a particular firm size, industry or country setting. Then again, this induces additional layers of heterogeneity to the dataset, which may not be completely captured by control variables. Most standard regression models require homoscedasticity for consistent estimation results.[65] That is, the variance of the random variable is assumed to be the same regardless of whether observations stem from large or small firms and of how they differ by industry or country. If this is not the case, estimations might suffer from heteroscedasticity. Heteroscedastic datasets may lead to an underestimation of the variance in an empirical model and subsequently to a lower threshold for the identification of significant results. Given the nature of our dataset, we consider it necessary to test for homoscedasticity. We apply Likelihood ratio tests to check if firm size, industry and loca-

[65] See Greene (2002), p. 698-700, for details in the context of Tobit models.

tion of a firm cause heteroscedasticity.[66] The results of the LR test reject homoscedasticity in all model specifications. Thus we include firm size, country dummies and industry dummies in heteroscedastic regressions where we consider the variance σ_i^2 of observation i to be of the form $\sigma_i^2 = \sigma exp(z_i'a)$. The vector of variables in the heteroscedasticity term is represented by z while a denotes the vector of additional coefficients to be estimated. This correction allows for the estimation of heteroscedasticity-consistent coefficients.

In addition, we inspect the dataset for issues arising from multicollinearity by calculating both pair-wise correlations and variance inflation factors. The dataset shows no particularly high degree of multicollinearity by any conventionally applied standard in the literature (Chatterjee and Hadi, 2006).[67]

4.4 Results

4.4.1 Descriptive statistics

Table 4.4 shows interesting differences in firms' knowledge search with respect to innovation success. We conduct significance tests on mean differences between firms with above average usage of certain types of knowledge search compared with the rest. Firms using science-driven knowledge search at an above average level exhibit a significantly higher share of sales of both market and firm novelties. In contrast, we do not observe a significant difference for firms engaging predominantly in a supplier-driven knowledge search. A somewhat mixed pattern is revealed by firms that mainly use a market-driven knowledge search. We find a higher share of sales of firm novelties while there is no observable difference in the share of sales of market novelties compared to firms that use a market-driven knowledge search to a below average extent.

However, firms differ along several dimensions with regard to their choice of type of knowledge search. Again, we test for significant mean differences between firms with an above average use of a particular type of search compared to their below average counterparts. Common to all types of knowledge search is the fact that they are significantly more likely to be chosen by firms with higher R&D spending and continuous

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[66] These variables have frequently been shown to cause heteroscedasticity in this setting (see. e. g. Aschhoff and Schmidt, 2008; Czarnitzki and Toole, 2007).

[67] The correlation matrix and the variance inflation factors are presented in Table D 3 in Appendix D.

R&D activities. Firms with above average search for external knowledge are also significantly larger (in terms of sales), which reflects the availability of resources to develop an active search for external knowledge.

Table 4.4: Descriptive statistics differentiated by type of knowledge search

	All firms		Science-driven search - above average use			Supplier-driven search - above average use		Market-driven search - above average use		
	Mean	Std. Dev.	Mean		Std. Dev.	Mean	Std. Dev.	Mean		Std. Dev.
Share of sales with market novelties	0.102	0.181	0.112	***	0.180	0.105	0.181	0.103		0.176
Share of sales with firm novelties	0.159	0.235	0.168	**	0.228	0.157	0.231	0.169	***	0.230
N	4,933		1,932			2,522		2,535		

Asterisks indicate the level of significance that the differences of sample means are not equal 0: * p<0.10, ** p<0.05, *** p<0.01. Results are derived from Two-sample t tests comparing sample means of above average and below average use. The descriptive statistics of the remaining variables is shown in Table D 1 in Appendix D.

Firms with above average science- and/or market-driven knowledge search are significantly more internationalized (measured as export share of sales) and part of a company group. Process innovators are more likely to focus on science-driven and/or supplier-driven knowledge search. With regard to differences across sectoral patterns, we find that science-driven knowledge search is significantly more attractive for firms in AKP and MPG. Supplier-driven knowledge search is more intensively used by SIS firms, and market-driven knowledge search again by AKP and MPG firms.

4.4.2 Regression results

Table 4.5 shows the results of the Tobit model estimations. As outlined previously, we correct the variance in each model to account for the effects of heteroscedasticity and test the outcomes of this correction successfully. We estimate two separate models for each dependent variable.

Columns I and II show the estimation results for the full sample. The results in column I show a positive relationship between success with new-to-market innovations, as measured by the share of sales of market novelties, both for science-driven and supplier-driven knowledge search. Thus, we find support for hypotheses 2, which states that science-driven knowledge search propel success with new-to-market innovations rather than with imitations. Column II shows that success with imitations, as measured by the share of sales of firm novelties, is positively affected by market-driven knowledge search while there is no impact on success of new-to-market innovations. This finding supports hypothesis 1 and implies a rejection of hypothesis 3. Supplier-driven knowledge search propels performance with new-to-market innovations but has no significant effect on imitations.

Table 4.5: Results of Tobit estimations for the full sample

	Share of sales of market novelties I	Share of sales of firm novelties II
Science-driven search (scale)	0.047**	0.022
	(0.022)	(0.025)
Supplier-driven search (scale)	0.046**	0.015
	(0.022)	(0.025)
Market-driven search (scale)	0.029	0.136***
	(0.019)	(0.022)
R&D intensity	0.326***	0.138**
	(0.058)	(0.067)
Continuous R&D activities[a]	0.090***	0.036***
	(0.010)	(0.011)
Export intensity	0.037**	0.012
	(0.017)	(0.019)
Sales 1998 (log)	-0.002	0.001
	(0.003)	(0.003)
Part of company group[a]	0.010	-0.001
	(0.009)	(0.011)
Process innovation[a]	0.000	-0.058***
	(0.009)	(0.010)
Constant	-0.177**	-0.086*
	(0.046)	(0.051)
Country dummies	included	included
Industry dummies	included	included
Wald-Test on joint significance of industry dummies	W(χ2(3)) = 4.99	W(χ2(3)) = 4.37
$R^2_{McFadden}$	0.14	0.12
N	4,933	4,933
LR/Wald chi2	306.82	288.90
P-value	0.00	0.00
Log likelihood	-1,872.29	-2,351.57
LR - Test on heteroscedasticity	LR(χ2(10)) = 3745***	LR(χ2(10)) = 4703***

[a] Dummy variable. Standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Search scales are rescaled between 0 and 1. Coefficients of sector and country dummies are presented in Table D 2 in Appendix D. Heteroscedasticity terms include 3 dummies for firm size measured by sales in 1998 (log) (0-24th percentile, 25th - 49th percentile, 50th -74th percentile), country dummies and industry dummies.

Regarding our control variables, we find – as expected – a positive effect of R&D intensity on both new-to-market innovation and imitation performance. Moreover, performing R&D continuously has a positive impact on both types of a firm's innovation success. Regarding the remaining control variables in our regression we find that higher export intensity goes hand in hand with higher new-to-market innovation performance while there is no significant effect on imitation success. This may reflect incentives to engage in new-to-market innovation due to high competition pressure in international markets. If firms are process innovators they have to allocate limited personnel and financial resources to the development of both new processes and new products. Therefore, innovation success in terms of sales will decrease, which is supported by our findings of negative effects of process innovation. However, this holds only for the models of imitation. No effects can be found for firm size and for a firm being part of a company group.

Table 4.6 shows the results of the Tobit estimations of the four major sectoral patterns. Several interesting similarities but also differences can be identified among the models. A first striking finding is that a market-driven knowledge search never propels innovation success with new-to-market innovations but only with imitations. This holds for the three sectoral patterns AKP, MPG and PGS. An exception is, however, SIS, which exhibits no significant effect of a market-driven knowledge search at all. Another interesting finding is that both a science-driven and a supplier-driven knowledge search are relevant for new-to-market innovation performance in AKP and SIS while we find no effect in MPG and PGS. Additionally, a science-driven search strategy also facilitates innovation performance with imitations in AKP. The results for the control variables are largely in line with the findings of the full sample estimations.

Table 4.6: Results of the Tobit estimations for the sectoral patterns

	AKP		***MPG***		***SIS***		***PGS***	
	Share of sales of market novelties	Share of sales of firm novelties	Share of sales of market novelties	Share of sales of firm novelties	Share of sales of market novelties	Share of sales of firm novelties	Share of sales of market novelties	Share of sales of firm novelties
	III	IV	V	VI	VII	VIII	IX	X
Science-driven search (scale)	0.074 *	0.092 **	0.027	-0.052	0.175 ***	0.019	-0.044	0.027
	(0.041)	(0.047)	(0.035)	(0.041)	(0.060)	(0.072)	(0.042)	(0.050)
Supplier-driven search (scale)	0.105 **	0.037	-0.005	0.018	0.103 **	-0.061	0.037	0.028
	(0.045)	(0.051)	(0.036)	(0.042)	(0.049)	(0.052)	(0.042)	(0.049)
Market-driven search (scale)	0.065	0.186 ***	0.015	0.142 ***	0.031	0.043	0.000	0.116 ***
	(0.040)	(0.045)	(0.032)	(0.037)	(0.043)	(0.047)	(0.038)	(0.043)
R&D intensity	0.180 ***	0.109	0.511 ***	0.294	0.992 **	1.220 **	1.397 ***	0.148
	(0.064)	(0.076)	(0.169)	(0.191)	(0.420)	(0.572)	(0.459)	(0.563)
Continuous R&D activities[a]	0.148 ***	0.028	0.079 ***	0.055 ***	0.039 *	0.016	0.064 ***	0.005
	(0.021)	(0.022)	(0.016)	(0.018)	(0.023)	(0.026)	(0.019)	(0.022)
Export intensity	0.025	0.025	0.051 *	0.024	-0.163 **	-0.088	0.097 ***	0.048
	(0.033)	(0.037)	(0.026)	(0.031)	(0.065)	(0.055)	(0.033)	(0.035)
Sales 1998 (log)	-0.017 ***	-0.003	0.002	0.008	0.003	0.007	0.011 *	-0.003
	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)
Part of company group[a]	0.001	0.012	0.011	-0.036 *	-0.007	0.038	0.020	-0.001
	(0.018)	(0.021)	(0.016)	(0.019)	(0.021)	(0.023)	(0.019)	(0.022)
Process innovation[a]	0.002	-0.031	-0.008	-0.042 **	-0.015	-0.068 ***	0.013	-0.087 ***
	(0.017)	(0.020)	(0.015)	(0.017)	(0.022)	(0.023)	(0.019)	(0.022)
Constant	0.021	-0.081	-0.173 **	-0.169 *	-0.233 ***	-0.058	-0.395 ***	0.015
	(0.087)	(0.100)	(0.077)	(0.088)	(0.087)	(0.095)	(0.117)	(0.108)
Country dummies	included	included	included	included	included	included	included	included
$R^2_{McFadden}$	0.19	0.08	0.12	0.11	0.18	0.20	0.16	0.15
N	1,164	1,164	1,702	1,702	800	800	1,267	1,267
LR/Wald chi2	120.82	55.29	88.90	103.43	43.57	47.91	78.26	86.74
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log likelihood	-423.56	-522.82	-582.15	-762.98	-292.07	-335.65	-498.62	-665.34
LR - Test on heteroscedasticity	LR(χ2(7)) = 847***	LR(χ2(7)) = 1046***	LR(χ2(7)) = 1164***	LR(χ2(7)) = 1526***	LR(χ2(7)) = 584***	LR(χ2(7)) = 671***	LR(χ2(7)) = 997***	LR(χ2(7)) = 1331***

[a] Dummy variable. Standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Search scales are rescaled between 0 and 1. Heteroscedasticity terms include 3 dummies for firm size measured by sales in 1998 (log) (0-24th percentile, 25th -49th percentile, 50th -74th percentile), country dummies and industry dummies.

4.5 Concluding remarks

Our research benefits from a comprehensive cross-country dataset, which allows us to draw conclusions beyond a certain industry or country context. However, we see room for improvement, which may provide pathways for future research. The effects of investments in R&D and open innovation networks may reach their full potential over the long run. Hence, longitudinal studies may help to test and substantiate some of our cross-sectional findings. Besides, qualitative studies may provide further in-depth insights into the mechanisms underlying the different types of knowledge search. In this respect it would be especially fruitful to explicitly capture the role of functional departments (especially marketing and procurement) and their interaction with the R&D department when certain knowledge sources are identified, activated and exploited. This may be especially relevant with regard to how legitimacy and trust can be established and how these mechanisms differ across varying knowledge sources. Finally, our investigation is limited to product innovation. Extending this line of research to other types of innovations like organizational or business model innovations may be a fruitful direction for further research.

5 Summary and conclusions

5.1 Summary

This thesis provides empirical evidence from Germany on the effects of vertical relations, competition and search strategies on different aspects of innovation behaviour. It is hence approaching central aspects of research on industrial organization and management.

In chapter 2 we study the effects of bargaining power in vertical relations on suppliers' R&D profitability and suppliers' innovation incentives. These questions have relevance for competition policy as they are often addressed when assessing effects of mergers in downstream markets or when investigating conduct in downstream markets with respect to impact upon upstream markets (see e. g. Competition Commission, 2008). In order to test the hypotheses, survey-based datasets are used which provide rich information on the relationships between suppliers and their buyers on the level of the supply firm. Oftentimes, researchers can only observe horizontal links between supply firms when investigating questions of both suppliers' profitability and innovation incentives. Hence additional information on their buyers provides a valuable opportunity to take vertical interactions into account.

Section 2.1 explores the relationship between a supplier's bargaining power and R&D profitability. Studies on the relationship between R&D, innovation and firm profitability mostly concentrate on the impact of horizontal market structure which follows traditional industrial organization literature that emphasizes the importance of market concentration and entry barriers for firm profitability. While providing inconclusive results, none of the existing studies took however the vertical interactions of R&D performers into account.

Building on theoretical and empirical evidence on the effects of bargaining in vertical relationships with respect to suppliers' profitability, the market position and the degree of concentration in the buyer portfolio are identified as the crucial determinants of a supplier's bargaining power. Regarding R&D profitability, the latter is expected to diminish returns from R&D, while the former is expected to increase it.

The hypotheses are tested using a sample of 472 German firms from manufacturing sectors. The empirical findings support all hypotheses and therefore highlight the importance of taking bargaining power in vertical relations into account when analysing R&D profitability. The estimated effects are considerable: for an average R&D performing supplier an increase of R&D intensity in 2010 by a percentage point would reduce profits by about 14 % in 2012 given he depends completely from the largest three buyers and does hold an average market share. Contrastingly, a monopolist R&D performing supplier with average buyer concentration would experience a profit increase by 10 % in 2012. What is more, the findings support the hypothesis of a lagged impact of R&D investments on a supplier's R&D profitability (Ravenscraft and Scherer, 1982).

In section 2.2 we subsequently analyse the relationship between buyer power and innovation incentives of supplying firms. While theory provides mixed results about this relationship, empirical studies typically find a negative correlation between buyer power and suppliers' innovation incentives. However, most studies are limited to certain industries and apply measures of buyer power generated either on an industry level or by subjective assessments of suppliers. Moreover, they do not consider the type of buyer market competition and likely effects on suppliers' innovation incentives.

We benefit from a dataset that in contrast to the dataset used in section 2.1 additionally provides data on the industry of the buyers. This allows taking account of downstream industry characteristics. What is more, the available data also allow distinguishing between different degrees of buyer power. Based on a sample of 1,036 firms across manufacturing and service industries, we find a negative effect of buyer power on a supplier's likelihood to invest in R&D for both measures applied. As expected, the effect is more pronounced for the measure indicating strong buyer power. Again we find considerable effects of buyers' bargaining power. We estimate that a switch from no buyer power to strong buyer power decreases the probability of a supplier to establish R&D activities on average by 27 %. Furthermore strong buyer power also reduces a supplier's R&D intensity. Here a switch from no buyer power to strong buyer power leads on average to a reduction by 37 %.

We also find downstream industry characteristics to have an impact on supplier's R&D incentives when using a sample of manufacturing firms. We find evidence that in manufacturing industries the demand-pull argument applies. That is, stronger downstream competition leads to higher demand for innovative intermediate goods, thereby increasing not only the likelihood of R&D investments but also the intensity of R&D investment on the supply side. In contrast, we find that suppliers have a lower likelihood to take up R&D activities if downstream R&D intensity is high. This is a reasonable finding considering that R&D projects often require a minimum investment. On one hand, the minimum investment is likely to be higher if buyers are strongly involved in R&D while it on the other hand has to be financed with internal cash-flow.

Finally, we also explore whether there are joint effects of buyer power and downstream industry characteristics on suppliers' innovation incentives. We interestingly find for the sample of manufacturing firms that the negative effect of buyer power on a supplier's R&D probability is mitigated by downstream competition. This can be explained by spillovers from buyers in a highly competitive environment to suppliers which are more likely to be absorbed if buyers are large. This will in turn improve the bargaining position of the supplier. Consequently the supplier has a higher incentive to innovate. We also find a negative joint effect of buyer power and downstream R&D intensity on a supplier's R&D intensity which is in line with the argument that suppliers with powerful buyers who invest heavily into R&D reduce their efforts in order to maintain their profitability.

Even though the studies presented in sections 2.1 and 2.2 utilize valuable datasets in terms of information on supplier-buyer relationships, our understanding of bargaining power, buyer power and the resulting effects on suppliers R&D profitability and innovation incentives is far from being complete. Part of this is due to missing information on buyer characteristics that go beyond their industry affiliation. Therefore it would be helpful if we knew about the size of the buyers, the share of inputs sourced from a particular supplier, the product market they are active in, concentration within these markets and so on. Observations of supplier-buyer relationships over a longer period in time would complement richer data on buyers and improve analysis of vertical relationships considerably. This also applies from an econometrical point of view as panel data attenuates issues of endogeneity which can hardly be overcome with cross-section data.

The relationship between competition and resulting innovation incentives is dealt with in chapter 3, which contributes to the existing research by analysing the nexus between product market competition and innovation at the firm level in Germany. The study makes use of panel data from 1997-2005 for 1,015 German companies and applies two measures for product market competition: traditional price-cost margins and the profit elasticity which was recently proposed by Boone (2007) as a measure of industry level competitive behaviour. The econometric approach deviates from most prior research in the way that we do not only consider the impact on R&D expenditure but distinguish the effect of product market competition on the decision to invest in R&D and on the amount of R&D given that the firm has decided to conduct R&D. Though this distinction has become popular as the first stage in the model by Crèpon et al (1998) that links innovation and productivity and has been employed in many cross-sectional studies, to the best of our knowledge, a similar approach to examine the relationship between competition and innovation using longitudinal data is only adopted by Artes (2009) for Spanish firms.

Recent theoretical contributions furthermore argue that the effect of competition on R&D also depends on firms' technological distance to the frontier as well as on the technological spread within an industry (Aghion et al., 2005, Acemoglu et al., 2006). Section 3 contributes to the empirical literature on competition and innovation since the estimation strategy takes account of both these factors as well. Moreover, we are able to distinguish constant and deviation effects of competition, technological distance and technological spread on innovation incentives.

The results do not support a u-shaped relationship between competition and innovation for German manufacturing firms. Instead, we find a high level of constant competition to negatively affect innovation incentives which supports Schumpeter's (1942) argument that intense competition reduces margins thereby reducing opportunities for financing innovation projects.

Firms in technologically very uneven sectors are found to have a lower probability of performing R&D. Having said that, the results also show that a high constant level of technological disparity is linked to higher R&D intensities. This can be explained by stronger R&D incentives for R&D performers in unlevelled sectors due to larger productivity differences between the firms within an unlevelled sector compared to rather equally productive firms in a levelled sector. Therefore, expected profits of R&D in an unlevelled sector are higher compared to a levelled sector once the R&D investment is sunk.

We also observe that a constantly high level of technological distance implies a lower probability for R&D activities which is countervailed by a positive effect of a short term increase in technological distance. The constant level of technological distance seems to be less important for the decision on the intensity of R&D. This finding reflects that the investment decision will have a long-term perspective while in contrast the decision on R&D intensity is rather a short-term decision.

Moreover the results show that both technological distance and competition are strongly related to each other and that an effect of competition on innovation incentives should not be considered separately from technological distance. Our findings support the argument of Aghion et al. (2005) that innovation incentives of technological laggards decrease if competition gets more intense. In addition, this study provides evidence that firm level measures of competition are preferable compared to industry level measures as a more precise measurement of changes in competition is possible.

In chapter 4 we conduct a study on the nature of firms' search for external knowledge and what effects practitioners can expect from applying them. We argue conceptually that different instances of knowledge search are not homogeneous with regard to the sources they encompass. In that sense, conceptualizations describing knowledge search along the dimensions of breadth and depth (Katila and Ahuja, 2002; Laursen and Salter, 2006) may underestimate the degree of heterogeneity among different knowledge sources. What is more, we integrate two additional elements into the stream of research on open innovation and search strategies. First, we focus on varying degrees of novelty in firms' open innovation performance. Some knowledge sources can be expected to provide knowledge with a higher degree of novelty providing more opportunities for new-to-market innovation than others. Second, the nature of innovation activities differs significantly across sectors. In a first step, we test our hypotheses empirically for a comprehensive sample of almost 5,000 firms from five Western European countries and find support for most of them. In a second step, we explore the effects of search on both types of innovation performance across four sectoral patterns of innovation which encompass both manufacturing and service firms.

From a research perspective, we introduce the notion of selectivity in firms' knowledge search. Neither breadth nor depth in a firm's search provide much guidance as to what knowledge sources to combine in a broad knowledge search and what ones to emphasize for depth. We find strong support for our theoretical argument that management should choose a certain direction for a firm's knowledge search. Science-driven, market-driven, and supplier-driven knowledge search differ significantly in the kind of knowledge they can provide and the way they can be accessed by the firm. They can therefore not be assumed to be substitutive.

This is reflected in the value they can provide in different sectors and with respect to different degrees of novelty. Several studies highlight the increasing importance of service sectors for most modern economies (e.g. Sirilli and Evangelista, 1998). Moreover, successful innovation in most sectors is increasingly based on a combination of novel products and services instead of a narrow focus on one or the other. However, empirical tests of open innovation knowledge search have primarily focused on manufacturing sectors (Katila and Ahuja, 2002; Laursen and Salter, 2006; Rosenkopf and Nerkar, 2001). We find considerable differences across the four sectoral patterns on which our analysis is based (Castellacci, 2008). It appears that firms can selectively influence their innovation performance depending on targeted search for external knowledge and their sectoral trajectories. In this respect, we find that market-driven knowledge search almost always increases imitation performance. It seems to be very limited in providing highly novel knowledge to firms that would consequently result in new-to-market innovations. Market-driven knowledge search thus includes the danger of over-emphasizing short-term customer needs and imitations of already existing products. Hence, our findings support existing literature (e.g. Slater and Narver, 1998): A primary strategy of avoiding “customer-led” traps of incremental innovation may rest in refocusing a firm’s knowledge pool with search directed at leading universities and specialized suppliers.

In contrast to this, firms adopting a science-driven or supplier-driven knowledge search have a good chance to create new-to-market innovations. Advanced knowledge providers can also propel imitation performance by relying on knowledge inputs from science. It seems that in this sectoral pattern the firm’s knowledge base needs to be regularly informed by novel insights from science to be able to even keep up with competitors and to successfully imitate their products.

5.2 Conclusions

As mentioned in the introduction, the evaluation of the Lisbon strategy shows that the goal to spend 3% of the GDP for R&D is clearly missed. Hence the successor of the Lisbon strategy, Europe 2020, is still pursuing the 3% goal as a means to develop an economy based on knowledge and innovation. In order to deliver the objectives of Europe 2020, the European Commission emphasizes that it is vital to enhance key instruments such as the single market. Therefore they are willing to make use of specific competition policy which is supposed to assure that efficient markets support competition thereby providing incentives for innovation and growth. Furthermore, Europe 2020 encompasses instruments by which the delivery of the strategy's objectives is backed up. The flagship initiative "Innovation Union" which is intended to enhance framework conditions for innovation and R&D on one hand and the accessibility of financial means for research and innovation on the other hand is one of these means. The implementation of this flagship initiative is supposed to ensure "that innovative ideas can be turned into products and services that create growth and jobs" (European Commission, 2010b; p. 12). To this end, the initiative encompasses among others actions on both EU and national level to support links between education (universities), business and research and innovation. The strengthening of these links is important as firms can benefit from connecting their own innovation activities to external know-how since doing so enables them to absorb innovation impulses from other players in the innovation system. The increasing adoption of such cooperative behaviour is in sharp contrast to research and development carried out merely within the bounds of an enterprise.

The instruments applied in Europe 2020, namely the creation of innovation incentives through competition as well as the strengthening of links between actors in the innovation system are the subject of interest of this thesis. It provides empirical evidence on the effects that can be expected to occur when these instruments are applied successfully.

The investigation of incentives emerging from competition on business innovation in chapter 3 shows that a first requirement for a successful competition policy is to make sure that competition can be properly measured. As we show the measured effects of competition on firms' innovation incentives in our study differ considerably, depending on which measure is used. We apply two different measures of competition, the *1-PCM* on firm level and the *PE* which is measured on industry level. Besides the theoretical drawbacks of the *1-PCM* (see Tirole, 1998 and Boone, 2008 as well as the references cited therein) this measure is easily computed and the data required is readily available in most datasets. Moreover it provides a competition measure at firm level.[68] Comple-

[68] Most datasets contain the required information to compute the PCM on firm level. If the firm is active in many product markets however, there is an aggregation problem as well since the PCM computed on firm level then reflects competition intensity in more than one market.

mentary, we use the profit elasticity (*PE*) proposed by Boone et al. (2007). *PE* is measured on industry level and is defined as the percentage fall in profits due to a percentage increase in costs. The aggregation problem of other measures of competition on industry level, e. g. concentration measures which may reflect an average over many heterogeneous product markets, are relevant for the *PE* as well. Therefore it is recommendable to compare the results of different measures and thus check their robustness.

We also show that changes in competition policy aiming at an increase of the average level of competition would lower innovation incentives according to our findings. This is due to the fact, that increased competition lowers margins and hence operating profits. As the latter are a common source to finance innovation projects, a reduction in profits implies less opportunity to innovate. In addition, activities of research and development usually have a long-term perspective. The decision to invest in such activities is hence determined by a firm's assessment how profitable resulting innovations may be in the future. If the level of competition increases in the long-term perspective, then the expected profitability of R&D activity decreases and firms' may rather refrain from investing in R&D. Therefore, the introduction of policy measures aiming at an increase in innovation and R&D spending by stimulating competition as postulated in the Horizon 2020 strategy would have negative effects on innovation incentives of German manufacturers.

In addition, a change in competition, e. g. by entry, and its impact on firms' innovation incentives will depend on the individual distance to the technological frontier. If the distance is too large, an increase in competition will affect innovation incentives negatively. Therefore, careful assessment is needed when policies concerned with the stimulation of competition are applied to industries with a small fraction of highly productive firms. While the very productive firms are likely to respond positively in terms of R&D engagement on intensifying competition, the less productive firms may either refrain from starting R&D or reduce their spending.

Increasing innovation incentives by competition policy also has to take vertical relationships between firms into account. The results of chapter 2 imply that firms profit from a diversified buyer structure in terms of increased profitability. This implies that a high degree of concentration on downstream markets adversely affects the opportunities for suppliers to invest in innovation. This is confirmed by the results of section 2.2 which show that buyer power lowers both firms' probability to start R&D activities and the amount of investment. There is a vast strand of literature reporting that firms in order to finance innovation projects rely heavily on their internal cash flow as the cost for external capital is oftentimes too high (for a survey see Hall and Lerner, 2010). Hence, competition authorities have to carefully investigate the possible adverse effects of mergers in the downstream market on supply markets. To this end, they have to account for the characteristics of the downstream industry. Section 2.2 shows that these also matter for the innovation incentives of suppliers.

Our results hint in the direction, that buyer power in combination with strong downstream competition does not necessarily lead to less upstream innovation incentives. In fact, strong buyer market competition may even spur innovation incentives if transferred to suppliers by a powerful buyer. European competition policy is focusing on the consumer though. That is, the impact of downstream mergers on suppliers is only of concern if competition authorities expect harm for the end user. The evaluation of merger effects on the supply market and the subsequent feedback effects on downstream markets as well as consumers appears to be a heroic task however.

The Commission moreover stated that “much of the current interest in buyer power highlights the plight and problems faced by small suppliers. It is clear that some of these concerns relate to issues that are not a matter of competition law but rather highlight social or political concerns” (OECD, 2008; p. 2). Hence the scope for competition policy to consider effects of downstream concentration on suppliers’ innovation incentives seems to be limited anyway.

The flagship initiative "Innovation Union" which is outlined in Europe 2020 is supposed to ensure “that innovative ideas can be turned into products and services that create growth and jobs” (European Commission, 2010b; p. 12). One of the aims of the flagship initiative is to support links between education (universities), business and research and innovation. The strengthening of these links is important as firms can benefit from connecting their own innovation activities to external know-how since doing so enables them to absorb innovation impulses from other players in the innovation system. How such links can be successfully exploited with respect to both an innovation’s degree of novelty as well as a firm’s sector of activity is shown chapter 4. In search for external knowledge firms should focus their search since not all types of knowledge search provide the basis for new-to-market innovations. Market-driven knowledge search provides imitations which may still be profitable without entailing the increased risk of the new-to-market innovations. The performance potentials of selective knowledge search for external knowledge are especially high for advanced knowledge providers and supporting infrastructural service sectors. Firms in these sectors should develop deeper ties with leading universities as well as suppliers. These activities require resource commitments in terms of financial investments (e.g. specialized labs) and human resources (e.g. joint research projects, sponsored PhD projects). The recognition of industry differences in our study is important because in all other sectors (MPG, PGS), the expected returns of external search cannot outweigh the costs. Consequently, firms in these sectors are better off fostering their internal R&D activities when it comes to generating new-to-market products.

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A Appendix: Bargaining in vertical relationships and suppliers' R&D profitability

Table A 1: Industry breakdown

Variable	Industry group	Nace Code[a]
IND1	Food/Tobacco	10-12
IND2	Textiles	13-15
IND3	Wood/Paper	16-17
IND4	Chemicals	20-21
IND5	Synthetics	22
IND6	Glass/Ceramics	23
IND7	Metal	24-25
IND8	Machinery	28, 33
IND9	Electronics	26-27
IND10	Automotive	29-30
IND11	Furniture/Sport/Toys (Reference group)	31-32

[a] Nace Code Rev. 2

Table A 2: Descriptive statistics differentiated by suppliers' R&D status (continued from Table 2.2)

	Full Sample		R&D performer		Non-R&D performer		T-test	
	Mean	SD	Mean	SD	Mean	SD		
IND1	0.066	0.248	0.025	0.156	0.125	0.332	4.39	***
IND2	0.053	0.224	0.029	0.167	0.089	0.285	2.88	**
IND3	0.057	0.232	0.018	0.133	0.115	0.319	4.53	***
IND4	0.091	0.288	0.125	0.331	0.042	0.200	-3.12	**
IND5	0.083	0.276	0.068	0.252	0.104	0.306	1.41	
IND6	0.074	0.262	0.071	0.258	0.078	0.269	0.27	
IND7	0.140	0.347	0.143	0.351	0.135	0.343	-0.23	
IND8	0.161	0.368	0.186	0.390	0.125	0.332	-1.77	*
IND9	0.169	0.376	0.236	0.425	0.073	0.261	-4.73	***
IND10	0.044	0.206	0.054	0.226	0.031	0.174	-1.15	
IND11	0.061	0.240	0.046	0.211	0.083	0.277	1.64	
N	472		280		192			

All variables are dummy variables. Columns with heading SD display standard deviations. The last two columns display t-statistics whether a T-test on mean difference between the respective group of R&D and non-R&D performers rejects the Null hypothesis of no difference. The asterisks indicate the corresponding level of significance (* 10 %, ** 5 %, *** 1 %).

Table A 3: Estimation results of heteroscedasticity consistent ordered Probit models (continued from Table 2.3)

	Dependent variable: Profit over sales							
	2011		2012		2011		2012	
	I		II		III		IV	
IND1	-0.626		-1.604		-0.770		-1.773	*
	(0.976)		(1.013)		(0.941)		(0.979)	
IND2	-0.516		-1.902	*	-0.637		-2.032	*
	(1.208)		(1.116)		(1.185)		(1.103)	
IND3	0.994		0.471		0.906		0.412	
	(1.472)		(1.386)		(1.471)		(1.403)	
IND4	3.970	***	2.176	*	4.150	***	2.207	*
	(1.410)		(1.315)		(1.413)		(1.328)	
IND5	0.347		-0.297		0.204		-0.450	
	(1.191)		(0.972)		(1.165)		(0.952)	
IND6	1.967		1.200		1.754		0.954	
	(1.370)		(1.281)		(1.342)		(1.248)	
IND7	-0.029		-0.862		-0.101		-0.942	
	(0.926)		(0.890)		(0.896)		(0.864)	
IND8	2.342	**	2.404	***	2.423	***	2.486	***
	(0.934)		(0.863)		(0.911)		(0.844)	
IND9	2.996	***	1.859		2.706	**	1.444	
	(1.154)		(1.191)		(1.127)		(1.137)	
IND10	0.498		0.494		0.331		0.245	
	(1.347)		(1.277)		(1.366)		(1.312)	
Wald - Test: joint significance of industry dummies	31.45	***	39.97	***	33.60	***	43.64	***
R^2_{McFadden}	0.81		0.81		0.80		0.80	
N	472		472		472		472	
Log likelihood	-919		-916		-915		-910	
LR-test on heteroscedasticity	LRχ2 (11) = 49.95	***	LRχ2 (11) = 54.79	***	LRχ2 (11) = 50.91	***	LRχ2 (11) = 54.41	***

All variables are dummy variables. Standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Heteroscedasticity term includes East and 10 industry dummies.

Table A 4: Estimation results of heteroscedasticity consistent ordered Probit models for a sample excluding small firms and a sample of R&D performing firms (continued from Table 2.4)

	Dependent variable: Profit over sales 2012							
	Small firms excluded				R&D performing firms			
	I		II		III		IV	
IND1	-2.478	*	-2.992	**	1.671		0.972	
	(1.321)		(1.202)		(2.118)		(2.094)	
IND2	-2.511	*	-2.647	*	-0.739		-0.913	
	(1.526)		(1.495)		(1.496)		(1.517)	
IND3	-0.069		-0.111		5.528		5.961	
	(1.590)		(1.563)		(5.736)		(5.836)	
IND4	0.589		0.093		3.291	**	2.881	*
	(1.625)		(1.466)		(1.641)		(1.624)	
IND5	-0.132		-0.669		-0.087		-0.143	
	(1.291)		(1.264)		(1.345)		(1.309)	
IND6	0.425		-0.025		2.981		2.830	
	(1.592)		(1.489)		(1.937)		(1.908)	
IND7	-0.588		-0.765		0.416		0.212	
	(1.148)		(1.086)		(1.373)		(1.314)	
IND8	1.567		1.520		2.508	*	2.583	**
	(1.130)		(1.079)		(1.322)		(1.270)	
IND9	1.639		0.491		3.272	**	2.760	*
	(1.497)		(1.408)		(1.653)		(1.575)	
IND10	0.281		0.080		0.649		0.109	
	(1.523)		(1.482)		(1.790)		(1.851)	
Wald - Test: joint significance of industry dummies	26.02	**	32.28	**	21.44	**	20.73	**
R^2_{McFadden}	0.52		0.75		0.59		0.65	
N	357		357		280		280	
Log likelihood	-687		-670		-530		-526	
LR-test on hetero-scedasticity:	$LR\chi2$ (11)= 38.56	***	$LR\chi2$ (11)= 37.49	***	$LR\chi2$ (16)= 68.91	***	$LR\chi2$ (16)= 66.64	***

All variables are dummy variables. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Hetero-scedasticity term for the sample in columns I and II includes East and 10 industry dummies while it includes 5 size dummies, East and 10 industry dummies for the sample in columns III and IV.

Table A 5: Correlation matrix and variance inflation factors

		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
A	PROFIT 2012	1														
B	PROFIT 2011	0.737	1													
C	RDINT	0.048	0.073	1												
D	MSHARE	0.169	0.156	0.102	1											
E	BUYCON	-0.046	-0.069	0.054	0.093	1										
F	SUBSTIT[a]	-0.196	-0.184	-0.201	-0.115	-0.076	1									
G	ELAST_L[a]	0.102	0.105	-0.022	0.133	-0.078	-0.151	1								
H	ELAST_M[a]	-0.107	-0.114	-0.027	-0.146	0.007	0.173	-0.671	1							
I	ELAST_H[a]	-0.119	-0.098	0.024	-0.002	0.077	0.093	-0.262	-0.324	1						
J	COMP[a]	0.175	0.121	0.020	0.119	0.068	-0.090	0.072	-0.045	-0.025	1					
K	DIVERS	-0.035	0.038	0.057	-0.103	-0.160	-0.087	0.001	-0.021	-0.021	0.083	1				
L	EXPORT	0.146	0.171	0.173	0.097	-0.056	-0.208	0.056	-0.056	-0.067	0.150	0.055	1			
M	SIZE	0.014	0.016	0.015	-0.022	-0.129	-0.038	-0.029	0.041	-0.039	0.064	0.089	0.286	1		
N	FOREIGN[a]	-0.107	-0.028	-0.034	-0.004	-0.042	0.016	-0.003	-0.045	0.077	0.002	-0.014	0.149	0.006	1	
O	EAST[a]	0.020	0.008	0.146	-0.035	0.197	-0.006	-0.126	0.077	0.0361	-0.041	-0.129	-0.179	-0.168	-0.067	1
VIF		2.41	2.31	1.25	1.12	1.20	1.21	3.63	3.91	2.30	1.11	1.16	1.33	1.16	1.08	1.17
Mean VIF		1.76														
N		472														

[a] Dummy variable. Correlations and variance inflation factors of industry dummies are not presented but available from the author upon request.

B Appendix: Buyer power and suppliers' incentives to innovate

B.1 Calculation of buyer market competition measures

PCM and R&D intensity are calculated for domestic and international markets. For domestic industries both measures are calculated on 2-digit-level Nace rev. 1.1 (except for Nace 24, which is separated in 244 pharmaceuticals and other chemicals) using MIP data. The PCM is calculated as given in equation (B.1). s_{it} represents sales, m_{it} material costs and w_{it} wages and salaries in industry *i* and year *t*. For German data we take the average over the time period from 2001 to 2004.

$$PCM_i^{GER} = \frac{1}{4}\sum_t \left(\frac{s_{it} - m_{it} - w_{it}}{s_{it}}\right) \tag{B.1}$$

The calculation of domestic R&D intensity is carried out as shown in equation (B.2) with RD_{it} denoting R&D expenditure of industry *i* in year *t*. Taking the average over the years 2001 to 2004 yields $RDint_i^{GER}$.

$$RDint_i^{GER} = \frac{1}{4}\sum_t \left(\frac{RD_{it}}{s_{it}}\right) \tag{B.2}$$

For customers in foreign countries we calculate the buyer market competition measures from OECD's Structural Analysis Database (STAN). We use information on the year 2003 from 19 OECD countries which represent the vast majority of export markets of the German economy: USA, France, United Kingdom, the Netherlands, Japan, Italy, Spain, Belgium, Korea, Austria, Sweden, Denmark, Finland, Greece, Norway, Ireland, Poland, Czech Republic and Hungary. The PCM on Nace 2 industry level (with the exception of Nace 244) is calculated as shown in equation (B.3). go_{cit} denotes gross output while ii_{cit} and $lcomp_{cit}$ account for expenditure on intermediate inputs and labour compensation of employees, respectively. The values refer to industry *i* in year *t* and country *c*.

$$PCM_i^{OECD} = \frac{\sum_c go_{ci} - ii_{ci} - lcomp_{ci}}{\sum_c go_{cit}} \tag{B.3}$$

Data on the R&D intensity of buyers in international markets is taken from OECD's Analytical Business Enterprise Research and Development (ANBERD) data base and linked to STAN. The year 2003 is used as reference year.

$$RDint_i^{OECD} = \frac{\sum_c RD_{ci}}{\sum_c go_{ci}} \tag{B.4}$$

The calculation of the R&D intensity for international markets is carried out as shown in equation (B.4). RD_{ci} represents the R&D expenditure in country *c* and industry *i* in the reference year.

Finally, the international values are weighted with firm *i*'s export share of sales while the domestic values of PCM and RDint are weighted with firm *i*'s share of domestic sales. The sum of both parts yields the variables used for the estimations.

B.2 Additional Tables

Table B 1: Industry breakdown

Variable	Industry Group	Nace Code[a]
IND1	Food/Tobacco	15, 16
IND2	Textiles	17, 18, 19
IND3	Wood/Paper/Printing	20, 21
IND4	Chemicals	24
IND5	Synthetics	25
IND6	Glass/Ceramics	26
IND7	Metal	27, 28
IND8	Machinery	29, 33.3
IND9	Electronics	30, 31, 32, 33.2, 33.4, 33.5
IND10	Automotive	34, 35
IND11	Furniture/Sport/Toys	33.1, 36
IND12	Wholesale	51
IND13	Transportation	60, 61, 62, 63, 64.1
IND14	Media Services	22.1
IND15	Computer/Telecomm.	64.3, 72.1, 72.2, 72.3, 72.4, 72.6
IND16	Financial Services	65, 66, 67
IND17	Consulting	74.1, 74.4
IND18	Techn. Services	74.2, 74.3
IND19	Enterprise Services (Reference group)	70.3, 74.5, 74.6, 74.7, 74.8

[a] Nace Rev. 1.1

Table B 2: Variable definitions

Variable	Definition
RD_{t+1}	Dummy variable taking value 1, if firm reports to have R&D expenditure in 2005 and 0 otherwise.
$RDINT_{t+1}$	R&D expenditure in 2005 divided by employees in 2005.
BP_L	Dummy variable taking value 1, if firm reports to generate at least 50% of the sales in 2004 with the largest 3 customers and 0 otherwise.
BP_H	Dummy variable taking value 1 if a firm reports to generate at least 50% of the sales in 2004 with the largest 3 customers and reports either to have more than 5 competitors or to have highly substitutable products. If one condition is not fulfilled the dummy takes the value 0.
BUYPCM[a]	1 – PCM on 2-digit level (Nace Rev. 1.1) and 3-digit level for Nace 244.
BUYRDINT[a]	Industry R&D intensity on 2-digit level (Nace Rev. 1.1) and 3-digit level for Nace 244.
$NOCOMP_t$	Dummy variable taking value 1 if firm reports to have no competitors on the main product market in 2004. Otherwise the dummy takes the value 0.
$COMP_t$	Dummy variable taking value 1 if firm reports to have 1 to 5 competitors on the main product market in 2004. Otherwise the dummy takes the value 0.
$DIVERS_t$	1 – share of sales in 2004 generated by the main product line.
$SIZE_t$	Log of number of employees in 2004 (full time equivalents).
AGE_t	Log of the number of years (in 2004) since the enterprise was founded.
$GROUP_t$	Dummy variable taking the value 1, if firm reports to be part of an enterprise group in 2004 and 0 otherwise.
$EAST_t$	Dummy variable taking the value 1, if firm are located on the former GDR territory or in West-Berlin in 2004 and 0 otherwise.

[a] For further explanations see Appendix B.1.

Table B 3: Industry breakdown of suppliers' largest customers

Variable	Industry group of largest buyer	NACE Code[a]
BUYIND1	Raw materials	10-11, 13-14, 17.1, 21.1, 23.2-23.3, 24.1, 26.5, 27.1, 37.1-37.2, 40-41
BUYIND2	Industry intermediates	15.7, 17.2, 17.5-17.6, 18.3, 19.1, 20.1-20.4, 21.2, 22.2, 24.2-24.7, 25.1-25.2, 26.1-26.4, 26.6-26.8, 27.2-27.5, 28.4-28.7, 31.2-31.6, 32.1, 34.3
BUYIND3	Capital goods	28.1-28.3, 29-30, 31.0-31.1, 32.2, 33, 34.1-34.2, 35.1-35.3
BUYIND4	Consumer goods	15.1-15.6, 15.8-15.9, 16.0, 17.3-17.4, 17.7, 18.1-18.2, 19.2-19.3, 20.5, 22.1, 22.3, 24.4-24.5, 29.7, 31.5, 32.3, 33.5, 35.4-35.5, 36.1-36.6
BUYIND5	Enterprise services	45, 51, 60.2-60.3, 61.1-61.2, 62.2-62.3, 63.1-63.2, 63.4, 64.1, 65.1-65.2, 66, 67.1, 71.2-71.3, 72.1-72.4, 72.6, 73.1-73.2, 74.1-74.8, 90, 92.1, 92.4
BUYIND6	Consumer services (Reference group)	45.4, 50, 52, 55, 60.1, 62.1, 63.3, 64.2-64.3, 67.2, 70.1-70.3, 71.1, 71.4, 72.5, 80.4, 92.2-92.3, 92.6-92.7, 93

[a] Nace Rev. 1.1.

Table B 4: Descriptive statistics differentiated by a supplier's R&D status (continued from Table 2.6)

	Full Sample		R&D performer		Non-R&D performer		T-test	
	Mean	SD	Mean	SD	Mean	SD	t-value	
IND1	0.032	0.176	0.025	0.157	0.038	0.19	1.122	
IND2	0.038	0.19	0.036	0.186	0.039	0.194	0.301	
IND3	0.049	0.216	0.046	0.21	0.052	0.222	0.412	
IND4	0.047	0.212	0.080	0.271	0.020	0.139	-4.590	***
IND5	0.056	0.23	0.057	0.232	0.055	0.229	-0.095	
IND6	0.025	0.156	0.023	0.15	0.027	0.162	0.377	
IND7	0.126	0.333	0.111	0.315	0.139	0.347	1.348	
IND8	0.091	0.287	0.128	0.335	0.059	0.236	-3.890	***
IND9	0.124	0.329	0.204	0.403	0.055	0.229	-7.418	***
IND10	0.024	0.154	0.023	0.15	0.025	0.156	0.197	
IND11	0.025	0.156	0.040	0.196	0.013	0.111	-2.820	***
IND12	0.050	0.218	0.023	0.15	0.073	0.261	3.702	***
IND13	0.086	0.28	0.025	0.157	0.138	0.345	6.553	***
IND14	0.034	0.181	0.021	0.144	0.045	0.207	2.101	**
IND15	0.043	0.204	0.067	0.251	0.023	0.151	-3.480	***
IND16	0.019	0.138	0.021	0.144	0.018	0.133	-0.367	
IND17	0.036	0.186	0.017	0.129	0.052	0.222	3.034	***
IND18	0.045	0.208	0.040	0.196	0.050	0.218	0.777	
IND19	0.049	0.216	0.013	0.112	0.080	0.182	5.080	***
BUYIND1	0.087	0.282	0.084	0.278	0.089	0.285	0.299	
BUYIND2	0.146	0.353	0.155	0.363	0.138	0.345	-0.816	
BUYIND3	0.297	0.457	0.338	0.474	0.263	0.44	-2.664	***
BUYIND4	0.110	0.313	0.103	0.304	0.116	0.321	0.673	
BUYIND5	0.203	0.402	0.191	0.394	0.213	0.409	0.850	
BUYIND6	0.157	0.337	0.128	0.335	0.182	0.386	2.383	**
N	1,036		476		560			

All variables are dummy variables. Columns with heading SD display standard deviations. The last two columns display t-statistics whether a T-test on mean difference between the group of R&D performers and non-R&D performers rejects the Null hypothesis of no difference. The asterisks indicate the corresponding level of significance (* 10%, ** 5 %, *** 1 %).

Table B 5: Estimation results of generalised Tobit models using different specifications of buyer power (continued from Table 2.7)

	Selection: $RD_{i,t+1}$				Intensity: $RDINT_{i,t+1}$			
	I		II		III		IV	
	BP_L		BP_H		BP_L		BP_H	
IND1	0.809	**	0.810	**	2.83	***	2.862	***
	(0.344)		(0.344)		(0.720)		(0.718)	
IND2	1.19	***	1.159	***	2.711	***	2.702	***
	(0.321)		(0.320)		(0.697)		(0.692)	
IND3	0.971	***	0.955	***	2.794	***	2.78	***
	(0.304)		(0.304)		(0.674)		(0.672)	
IND4	2.012	***	2.024	***	4.604	***	4.62	***
	(0.320)		(0.321)		(0.747)		(0.745)	
IND5	1.184	***	1.186	***	3.201	***	3.207	***
	(0.298)		(0.299)		(0.678)		(0.677)	
IND6	0.794	**	0.79	**	2.776	***	2.765	***
	(0.358)		(0.358)		(0.733)		(0.734)	
IND7	0.869	***	0.855	***	3.1	***	3.091	***
	(0.267)		(0.267)		(0.620)		(0.618)	
IND8	1.499	***	1.484	***	4.208	***	4.197	***
	(0.282)		(0.282)		(0.702)		(0.699)	
IND9	1.959	***	1.944	***	4.643	***	4.637	***
	(0.276)		(0.276)		(0.729)		(0.725)	
IND10	0.776	**	0.746	**	3.327	***	3.306	***
	(0.365)		(0.365)		(0.751)		(0.748)	
IND11	1.877	***	1.874	***	3.662	***	3.662	***
	(0.365)		(0.366)		(0.789)		(0.787)	
IND12	0.619	*	0.616	*	2.121	***	2.109	***
	(0.318)		(0.319)		(0.653)		(0.653)	
IND13	0.223		0.210		1.206	*	1.189	*
	(0.296)		(0.296)		(0.642)		(0.641)	
IND14	0.605	*	0.599	*	2.592	***	2.579	***
	(0.337)		(0.338)		(0.693)		(0.693)	
IND15	1.976	***	1.964	***	4.589	***	4.595	***
	(0.314)		(0.314)		(0.749)		(0.744)	
IND16	1.384	***	1.374	***	3.031	***	3.025	***
	(0.386)		(0.386)		(0.779)		(0.778)	
IND17	0.79	**	0.779	**	3.375	***	3.37	***
	(0.344)		(0.344)		(0.710)		(0.708)	
IND18	1.217	***	1.193	***	4.024	***	3.993	***
	(0.311)		(0.311)		(0.670)		(0.668)	
BUYIND1	0.102		0.090		-0.015		-0.020	
	(0.201)		(0.201)		(0.306)		(0.307)	
BUYIND2	0.349	*	0.340	*	0.325		0.326	
	(0.180)		(0.180)		(0.282)		(0.282)	
BUYIND3	0.415	**	0.410	**	0.072		0.08	
	(0.176)		(0.176)		(0.271)		(0.271)	
BUYIND4	0.286		0.287		0.445		0.451	
	(0.193)		(0.194)		(0.300)		(0.300)	
BUYIND5	0.314	*	0.319	**	0.424		0.434	
	(0.162)		(0.163)		(0.268)		(0.269)	
Wald-Test for joint significance of industry dummies	156.36	***	155.81	***	80.24	***	80.84	***
N	1,036		1,036		1,036		1,036	
LR/Wald $\chi 2$	112		111		112		111	
P-value	0.000		0.000		0.000		0.000	

All variables are dummy variables. Standard errors are shown in parentheses. Standard errors in column III and IV are corrected for the inclusion of the inverse Mills Ratio. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively.

Table B 6: Estimated coefficients of the generalised Tobit model for a sample of manufacturing firms using different specifications of buyer power (Continued from Table 2.8)

	Selection: $RD_{i,t+1}$				Intensity: $RDINT_{i,t+1}$			
	I		II		III		IV	
	BP_L		BP_H		BP_L		BP_H	
IND1	-1.089	***	-1.081	***	-0.607		-0.535	
	(0.377)		(0.377)		(0.542)		(0.544)	
IND2	-0.755	**	-0.779	**	-0.745		-0.73	
	(0.354)		(0.353)		(0.486)		(0.488)	
IND3	-0.984	***	-0.995	***	-0.611		-0.626	
	(0.345)		(0.346)		(0.473)		(0.472)	
IND4	0.082		0.097		0.96	**	0.985	**
	(0.356)		(0.357)		(0.390)		(0.390)	
IND5	-0.783	**	-0.776	**	-0.337		-0.329	
	(0.336)		(0.337)		(0.442)		(0.441)	
IND6	-1.247	***	-1.25	***	-0.665		-0.697	
	(0.393)		(0.394)		(0.568)		(0.566)	
IND7	-1.156	***	-1.166	***	-0.366		-0.38	
	(0.312)		(0.313)		(0.447)		(0.446)	
IND8	-0.558	*	-0.572	*	0.592		0.575	
	(0.325)		(0.326)		(0.385)		(0.385)	
IND9	-0.035		-0.047		0.937	***	0.935	***
	(0.314)		(0.314)		(0.353)		(0.353)	
IND10	-1.381	***	-1.408	***	-0.225		-0.242	
	(0.406)		(0.406)		(0.565)		(0.563)	
BUYIND1	0.333		0.337		0.048		0.066	
	(0.289)		(0.290)		(0.378)		(0.378)	
BUYIND2	0.798	***	0.786	***	0.17		0.189	
	(0.242)		(0.242)		(0.353)		(0.350)	
BUYIND3	0.778	***	0.778	***	0.023		0.058	
	(0.242)		(0.243)		(0.344)		(0.343)	
BUYIND4	0.646	**	0.648	**	0.347		0.367	
	(0.266)		(0.267)		(0.377)		(0.377)	
BUYIND5	0.769	***	0.78	***	0.451		0.477	
	(0.231)		(0.232)		(0.353)		(0.353)	
Wald-Test for joint significance of industry dummies	69.92	***	70.25	***	44.52	***	44.83	***
N	660		660		660		660	
LR/Wald $\chi 2$	76		77		76		77	
P-value	0.000		0.000		0.000		0.000	

All variables are dummy variables. Standard errors are shown in parentheses. Standard errors in column III and IV are corrected for the inclusion of the inverse Mills Ratio. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively.

Table B 7: Estimation results of generalised Tobit models including interactions between buyer power and downstream industry characteristics (continued from Table 2.9)

	Selection: $RD_{i,t+1}$		Intensity: $RDINT_{i,t+1}$	
	I	II	III	IV
	BP_L	BP_H	BP_L	BP_H
IND1	-1.162 ***	-1.138 ***	-0.659	-0.746
	(0.382)	(0.381)	(0.548)	(0.545)
IND2	-0.781 **	-0.814 **	-0.763	-0.753
	(0.357)	(0.355)	(0.486)	(0.482)
IND3	-0.996 ***	-1.013 ***	-0.605	-0.661
	(0.347)	(0.347)	(0.472)	(0.465)
IND4	0.109	0.111	0.976 **	0.942 **
	(0.359)	(0.359)	(0.390)	(0.383)
IND5	-0.771 **	-0.772 **	-0.327	-0.295
	(0.338)	(0.338)	(0.439)	(0.433)
IND6	-1.290 ***	-1.286 ***	-0.676	-0.686
	(0.393)	(0.394)	(0.569)	(0.559)
IND7	-1.179 ***	-1.190 ***	-0.377	-0.4
	(0.314)	(0.314)	(0.447)	(0.440)
IND8	-0.548 *	-0.576 *	0.606	0.524
	(0.327)	(0.327)	(0.384)	(0.378)
IND9	-0.045	-0.055	0.929 ***	0.888 **
	(0.316)	(0.316)	(0.354)	(0.347)
IND10	-1.434 ***	-1.435 ***	-0.234	-0.345
	(0.408)	(0.406)	(0.565)	(0.557)
BUYIND1	0.252	0.287	0.017	0.056
	(0.291)	(0.291)	(0.375)	(0.370)
BUYIND2	0.751 ***	0.757 ***	0.136	0.157
	(0.244)	(0.244)	(0.348)	(0.342)
BUYIND3	0.729 ***	0.742 ***	0.001	0.055
	(0.243)	(0.244)	(0.339)	(0.334)
BUYIND4	0.572 **	0.611 **	0.318	0.339
	(0.269)	(0.268)	(0.373)	(0.369)
BUYIND5	0.694 ***	0.738 ***	0.402	0.406
	(0.234)	(0.234)	(0.347)	(0.344)
Wald-Test for joint significance of industry dummies	72.47 ***	72.08 ***	44.94 ***	44.09 ***
N	660	660	660	660
LR/Wald $\chi 2$	77	86	77	86
P-value	0.000	0.000	0.000	0.000

All variables are dummy variables. Standard errors are shown in parentheses. Standard errors in column III and IV are corrected for the inclusion of the inverse Mills Ratio. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively.

C Appendix: Market incentives to innovate

C.1 Measurement of profit elasticity

We estimated profit elasticities using the model proposed by Boone et al. (2007). The original equation is given by:

$$\ln(\pi_{it}) = \alpha_i + \beta_1 \ln(c_{it}) + \beta_2 \ln(emp_{it}) + \varepsilon_{it}$$

Profits of firm *i* in period *t* are denoted with π_{it} and measured by the difference between sales, material costs (including energy costs) and wages and salaries. The firm specific fixed effect is represented by α_i. The marginal costs are approximated by the expression c_{it} which represents the sum of material costs (including energy costs) and wages and salaries divided by sales. The number of full time employees is measured by emp_{it}. The profit elasticity, i. e. the percentage change of profits if marginal costs increase by one percent, is then given by β_1. To allow β_1 to vary by year we adopt the following adjustment:

$$\ln(\pi_{it}) = \alpha_i + \sum_t \lambda_t [\beta_1 \ln(c_{it}) + \beta_2 \ln(emp_{it})] + \varepsilon_{it}$$

This specification includes additional year dummies denoted with λ_t. Using the comprehensive dataset provided by the CSS, we run Fixed Effect estimations for each Nace 3-digit-industry and yield thus negative profit elasticities for each industry and year. For the ease of interpretation we use the absolute value of the profit elasticity, i. e. an increase in the absolute value can be interpreted as an increase in the level of competition.

C.2 Measurement of total factor productivity

We estimate a firm specific production function and subsequently compute the total factor productivity as residual. This method is well described in the relevant literature (see the overview by Mairesse and Sassenou, 1991). The estimation equation of the log-transformed production function is given by:

$$\ln(y_{it}) = \alpha_i + \beta_1 \ln(k_{it}) + \beta_2 \ln(m_{it}) + \beta_3 \ln(l_{it}) + \gamma_n + t_t + \varepsilon_{it}$$

The sales per employee of firm i in period t with are represented by y_{it} while k_{it} denotes the capital intensity measured by tangible assets divided by employees. The material costs per employee are given by m_{it} and the employees are represented by l_{it}. We also include industry dummies which are denoted by γ_n and year dummies which are represented by t_t. The firm fixed effect is captured by the term α_i. To estimate the production function we use information on all firms included in the sample.

After estimating the production function, the total factor productivity can be calculated as residual. The equation given above changes to:

$$\varepsilon_{it} = \ln(y_{it}) - \beta_1 \ln(k_{it}) - \beta_2 \ln(m_{it}) - \beta_3 \ln(l_{it}) - \gamma_n - t_t - \alpha_i$$

Hence, we obtain a firm specific total factor productivity which is changing by year. Note that we estimate the TFP for all MIP firms available, i. e. we use a larger sample consisting of about 13,900 observations from roughly 5,000 firms. By doing so, we make sure to have a representative picture of the technological situation within an industry.

C.3 Estimation results applying *PE*

Table C 1: Estimation results of the Random Effects Probit using *PE*

	Dependent variable: RD_{it}							
	I		II		III		IV	
PE_{t-1}	0.423		0.142		0.319	**	-0.062	
	(0.261)		(0.105)		(0.151)		(0.415)	
PE_{t-1} x PE_{t-1}	-0.052							
	(0.044)							
DTF_{t-1}	0.578	**	0.566	*	1.302	**	0.571	**
	(0.290)		(0.289)		(0.529)		(0.290)	
$SDDTF_{t-1}$	-1.122		-1.051		-0.920		-2.959	
	(1.052)		(1.042)		(1.043)		(3.955)	
PE_{t-1} x DTF_{t-1}					-0.308	*		
					(0.184)			
PE_{t-1} x $SDDTF_{t-1}$							0.837	
							(1.649)	
CAP (ln) $_{t-1}$	0.001		0.003		0.003		0.003	
	(0.042)		(0.042)		(0.042)		(0.042)	
GP^{a}_{t}	-0.082		-0.081		-0.078		-0.081	
	(0.088)		(0.088)		(0.088)		(0.088)	
$\overline{PE}$	-0.040		-0.046		-0.042		-0.043	
	(0.097)		(0.096)		(0.096)		(0.095)	
$\overline{DTF}$	-0.859	**	-0.842	**	-0.838	**	-0.852	**
	(0.385)		(0.384)		(0.385)		(0.384)	
$\overline{SDDTF}$	-4.757	*	-4.584	*	-4.623	*	-4.829	*
	(2.766)		(2.772)		(2.778)		(2.855)	
$\overline{SIZE}$	0.362	***	0.363	***	0.361	***	0.363	***
	(0.036)		(0.036)		(0.036)		(0.036)	
$\overline{CAP}$	0.074		0.074		0.076		0.072	
	(0.060)		(0.059)		(0.059)		(0.059)	
$\overline{EAST}$	0.298	***	0.293	***	0.292	***	0.295	***
	(0.090)		(0.090)		(0.090)		(0.090)	
Constant	-0.770		-0.509		-0.976		0.026	
	(0.806)		(0.765)		(0.821)		(1.368)	
Wald-Test: joint significance of PE, DTF/SDDTF and interaction terms	$\chi2$ (2) = 3.17				$\chi2$ (3) = 8.26	**	$\chi2$ (3) = 2.89	
N	3,085		3,085		3,085		3,085	
Wald Chi	360		359		362		361	
Log likelihood	-1,568		-1,569		-1,567		-1,569	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. Robust and clustered standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Estimation includes 7 time dummies and 9 mean industry variables. Results of the remaining variables are presented in Table C 2 in Appendix C.3.

Table C 2: Estimation results of the Random Effects Probit using *PE* (continued from Table C 1)

	Dependent variable: RD_{it}							
	I		II		III		IV	
YEAR1999[a]	0.043		0.037		0.037		0.040	
	(0.051)		(0.051)		(0.052)		(0.052)	
YEAR2000[a]	0.314	***	0.307	***	0.307	***	0.307	***
	(0.103)		(0.102)		(0.103)		(0.102)	
YEAR2001[a]	0.229	*	0.211		0.204		0.210	
	(0.134)		(0.133)		(0.133)		(0.133)	
YEAR2002[a]	0.032		0.015		0.006		0.016	
	(0.116)		(0.114)		(0.114)		(0.114)	
YEAR2003[a]	0.040		0.022		0.013		0.023	
	(0.123)		(0.121)		(0.121)		(0.121)	
YEAR2004[a]	0.293	**	0.274	**	0.264	**	0.277	**
	(0.134)		(0.132)		(0.131)		(0.132)	
YEAR2005[a]	0.274	**	0.255	*	0.245	*	0.258	*
	(0.139)		(0.137)		(0.137)		(0.137)	
Mean IND2	-0.012		0.032		0.062		0.012	
	(0.235)		(0.230)		(0.230)		(0.229)	
Mean IND3	-0.334		-0.296		-0.257		-0.315	
	(0.217)		(0.216)		(0.218)		(0.220)	
Mean IND4	1.104	***	1.114	***	1.121	***	1.114	***
	(0.223)		(0.222)		(0.218)		(0.222)	
Mean IND5	0.431	*	0.494	**	0.524	**	0.476	**
	(0.224)		(0.217)		(0.218)		(0.221)	
Mean IND6	0.380		0.437	*	0.467	**	0.422	*
	(0.235)		(0.230)		(0.230)		(0.232)	
Mean IND7	0.252		0.295		0.333		0.275	
	(0.215)		(0.213)		(0.214)		(0.217)	
Mean IND8	0.880	***	0.932	***	0.974	***	0.920	***
	(0.229)		(0.224)		(0.225)		(0.226)	
Mean IND9	1.105	***	1.165	***	1.204	***	1.147	***
	(0.230)		(0.225)		(0.227)		(0.230)	
Mean IND10	1.535	***	1.599	***	1.624	***	1.581	***
	(0.253)		(0.247)		(0.247)		(0.251)	
N	3,085		3,085		3,085		3,085	
Wald Chi	360		359		362		361	
Log likelihood	-1,568		-1,569		-1,567		-1,569	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. Robust and clustered standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively.

Table C 3: Estimation results of the Random Effects OLS using *PE*

	Dependent variable: $RDINT_{it}$							
	I		II		III		IV	
PE_{t-1}	-0.016		-0.041		-0.193		-0.495	
	(0.352)		(0.114)		(0.161)		(0.535)	
PE_{t-1} x PE_{t-1}	-0.005							
	(0.059)							
DTF_{t-1}	-0.662	**	-0.661	**	-1.411	**	-0.661	**
	(0.297)		(0.297)		(0.619)		(0.298)	
$SDDTF_{t-1}$	-0.376		-0.374		-0.547		-4.907	
	(1.263)		(1.262)		(1.258)		(5.261)	
PE_{t-1} x DTF_{t-1}					0.300			
					(0.217)			
PE_{t-1} x $SDDTF_{t-1}$							1.864	
							(2.166)	
CAP (ln) $_{t-1}$	0.021		0.022		0.021		0.020	
	(0.041)		(0.041)		(0.041)		(0.041)	
GP^{a}_{t}	0.037		0.037		0.034		0.036	
	(0.094)		(0.094)		(0.094)		(0.094)	
$\overline{PE}$	-0.049		-0.049		-0.049		-0.044	
	(0.105)		(0.105)		(0.105)		(0.105)	
$\overline{DTF}$	-0.633	*	-0.634	*	-0.651	*	-0.630	
	(0.383)		(0.383)		(0.381)		(0.385)	
$\overline{SDDTF}$	5.842	*	5.854	*	6.082	*	5.276	
	(3.284)		(3.272)		(3.254)		(3.407)	
$\overline{SIZE}$	-0.102	**	-0.102	**	-0.104	**	-0.101	**
	(0.041)		(0.041)		(0.041)		(0.041)	
$\overline{CAP}$	0.009		0.009		0.007		0.009	
	(0.063)		(0.062)		(0.063)		(0.062)	
$\overline{EAST}$	0.295	***	0.294	***	0.294	***	0.295	***
	(0.096)		(0.096)		(0.096)		(0.096)	
Constant	-6.365	***	-6.339	***	-5.923	***	-5.074	***
	(0.913)		(0.869)		(0.893)		(1.795)	
Wald-Test: joint significance of PE, DTF/SDDTF and interaction terms	F(2,705) = 0.07				F(3,705) = 2.34	*	F(3,705) = 0.36	
N	1,954		1,954		1,954		1,954	
R^2	0.27		0.27		0.28		0.28	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. Robust and clustered standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Estimation includes 7 time dummies and 9 mean industry variables. Results of the remaining variables are presented in Table C 4 in Appendix C.3.

Table C 4: Estimation results of the Random Effects OLS using *PE* (continued from Table C 3)

	Dependent variable: $RDINT_{it}$							
	I		II		III		IV	
YEAR1999[a]	-0.288	***	-0.288	***	-0.290	***	-0.285	***
	(0.067)		(0.067)		(0.067)		(0.067)	
YEAR2000[a]	-0.304	***	-0.305	***	-0.308	***	-0.309	***
	(0.090)		(0.089)		(0.089)		(0.089)	
YEAR2001[a]	-0.298	**	-0.299	**	-0.296	**	-0.309	**
	(0.144)		(0.143)		(0.142)		(0.142)	
YEAR2002[a]	0.038		0.037		0.045		0.033	
	(0.123)		(0.122)		(0.121)		(0.121)	
YEAR2003[a]	-0.037		-0.038		-0.030		-0.037	
	(0.130)		(0.128)		(0.127)		(0.127)	
YEAR2004[a]	-0.094		-0.095		-0.086		-0.094	
	(0.140)		(0.138)		(0.137)		(0.137)	
YEAR2005[a]	-0.160		-0.161		-0.150		-0.158	
	(0.146)		(0.145)		(0.143)		(0.144)	
Mean IND2	0.504		0.508		0.463		0.459	
	(0.407)		(0.406)		(0.398)		(0.410)	
Mean IND3	0.197		0.199		0.157		0.159	
	(0.396)		(0.395)		(0.388)		(0.398)	
Mean IND4	1.621	***	1.621	***	1.617	***	1.620	***
	(0.390)		(0.390)		(0.386)		(0.389)	
Mean IND5	0.556		0.561		0.529		0.516	
	(0.406)		(0.403)		(0.397)		(0.405)	
Mean IND6	0.444		0.448		0.413		0.414	
	(0.441)		(0.438)		(0.432)		(0.440)	
Mean IND7	0.316		0.318		0.279		0.267	
	(0.384)		(0.383)		(0.377)		(0.389)	
Mean IND8	1.375	***	1.378	***	1.331	***	1.342	***
	(0.404)		(0.402)		(0.393)		(0.403)	
Mean IND9	1.495	***	1.499	***	1.459	***	1.452	***
	(0.408)		(0.406)		(0.398)		(0.409)	
Mean IND10	2.279	***	2.283	***	2.249	***	2.239	***
	(0.396)		(0.392)		(0.385)		(0.395)	
N	1,954		1,954		1,954		1,954	
R^2	0.27		0.27		0.28		0.28	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. Robust and clustered standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively.

C.4 Additional tables

Table C 5: Variable description

Variable	Definition
RD_t	Dummy variable taking unit value if firm *i* expensed a positive value on R&D in year *t* and zero otherwise.
$RDINT_t$	Logarithm of R&D expenditure over employees of firm *i* in year *t*.
$1\text{-}PCM_{t-1}$	$PCM_{t-1} = (PQ_{t-1} - M_{t-1} - W_{t-1} + RDexp_{t-1})/PQ_{t-1}$ with PQ_{t-1} denoting firm *i*'s sales in *t-1*, M_{t-1} representing the material costs (including energy costs), W_{t-1} denoting the wages and salaries and $RDexp_{t-1}$ denoting the R&D outlays of firm *i* in *t-1*. Then we calculate $1\text{-}PCM_{t-1}$.
PE_{t-1}	See Appendix B for a detailed description of the variable's generation.
DTF_{t-1}	See Appendix C for a detailed description of the variable's generation.
$SDDTF_{t-1}$	Standard deviation of the DTF within firm *i*''s Nace 2-digit industry in year *t-1*.
$SIZE_{t-1}$	Logarithm of the number of fulltime employees of firm *i* in year *t-1*.
CAP_{t-1}	Logarithm of firm *i*'s tangible assets divided by the number of employees in year *t-1*.
GP_t	Dummy variable taking unit value if firm *i* is part of an enterprise group in year *t* and zero otherwise.
$EAST_t$	Dummy variable taking unit value if in year *t* firm *i* is located in the part of Germany formerly constituting the German Democratic Republic and West-Berlin and zero otherwise.

Table C 6: Breakdown of industry classification

Industry	NACE code[a]	Industrydummy
Food / Tobacco	15 – 16	IND1 (Reference category)
Textiles	17 – 19	IND2
Paper / Wood / Print	20 – 22	IND3
Chemical	23 – 24	IND4
Plastics / Rubber	25	IND5
Glass / Ceramics	26	IND6
Metal	27 – 28	IND7
Machinery	29	IND8
Electricalengineering	30 – 32	IND9
Medicine / Optic / Processing	33	IND10
Vehicles[b]	34 – 35	IND10

[a] Two-digit dummy according to Nace Rev. 1.1. [b] Our panel contains only a few observations from industries 34-35. Therefore we use one dummy variable for industries 33-35.

Table C 7: Descriptive statistics differentiated by firms‘ R&D status (continued from Table 3.1)

	Full Sample		R&D performer		Non-R&D performer		T-test	
	Mean	SD	Mean	SD	Mean	SD		
YEAR 1998	0.165	0.371	0.158	0.364	0.177	0.382	1.3862	
YEAR 1999	0.172	0.378	0.169	0.375	0.177	0.382	0.5273	
YEAR 2000	0.100	0.299	0.116	0.321	0.071	0.256	-4.0722	***
YEAR 2001	0.083	0.276	0.088	0.283	0.076	0.265	-1.1111	
YEAR 2002	0.165	0.371	0.153	0.360	0.186	0.389	2.3951	**
YEAR 2003	0.143	0.350	0.133	0.340	0.160	0.367	2.0634	**
YEAR 2004	0.096	0.295	0.102	0.303	0.086	0.280	-1.5054	
YEAR 2005	0.076	0.266	0.081	0.273	0.068	0.252	-1.3382	
IND1	0.053	0.224	0.030	0.170	0.093	0.290	7.625	***
IND2	0.058	0.234	0.036	0.187	0.095	0.294	6.821	***
IND3	0.092	0.290	0.048	0.214	0.169	0.375	11.3918	***
IND4	0.090	0.286	0.107	0.310	0.060	0.238	-4.4384	***
IND5	0.102	0.303	0.097	0.296	0.111	0.315	1.2507	
IND6	0.062	0.241	0.055	0.228	0.074	0.262	2.1678	**
IND7	0.163	0.369	0.142	0.349	0.199	0.399	4.1564	***
IND8	0.160	0.367	0.194	0.396	0.102	0.302	-6.815	***
IND9	0.115	0.319	0.147	0.354	0.059	0.236	-7.423	***
IND10	0.104	0.306	0.143	0.350	0.037	0.189	-9.423	***
N	3,085		1,954		1,565			

All variables are dummy variables. Columns with heading SD display standard deviations. The last two columns display t-statistics whether a T-test on mean difference between the group of R&D performers and non-R&D performers rejects the Null hypothesis of no difference. The asterisks indicate the corresponding level of significance (* 10 %, ** 5 %, *** 1 %).

Table C 8: Estimation results of the Random Effects Probit using *1-PCM* (Continued from Table 3.3)

	Dependent variable: RD_{it}							
	I		II		III		IV	
YEAR1999[a]	0.048		0.049		0.048		0.049	
	(0.051)		(0.051)		(0.051)		(0.051)	
YEAR2000[a]	0.306	***	0.312	***	0.312	***	0.313	***
	(0.102)		(0.102)		(0.102)		(0.102)	
YEAR2001[a]	0.059		0.063		0.058		0.064	
	(0.104)		(0.103)		(0.103)		(0.103)	
YEAR2002[a]	-0.132		-0.131		-0.137		-0.130	
	(0.088)		(0.088)		(0.088)		(0.088)	
YEAR2003[a]	-0.132		-0.131		-0.134		-0.131	
	(0.093)		(0.093)		(0.093)		(0.093)	
YEAR2004[a]	0.128		0.132		0.125		0.131	
	(0.104)		(0.104)		(0.104)		(0.104)	
YEAR2005[a]	0.106		0.115		0.104		0.115	
	(0.117)		(0.117)		(0.117)		(0.117)	
Mean IND2	0.296		0.299		0.305		0.304	
	(0.246)		(0.246)		(0.248)		(0.250)	
Mean IND3	-0.086		-0.076		-0.070		-0.072	
	(0.232)		(0.232)		(0.234)		(0.235)	
Mean IND4	1.187	***	1.194	***	1.189	***	1.195	***
	(0.237)		(0.236)		(0.237)		(0.237)	
Mean IND5	0.673	***	0.689	***	0.697	***	0.694	***
	(0.232)		(0.232)		(0.233)		(0.235)	
Mean IND6	0.506	**	0.516	**	0.541	**	0.520	**
	(0.241)		(0.241)		(0.243)		(0.244)	
Mean IND7	0.571	**	0.581	**	0.583	**	0.586	**
	(0.227)		(0.227)		(0.229)		(0.231)	
Mean IND8	1.252	***	1.252	***	1.261	***	1.256	***
	(0.230)		(0.229)		(0.231)		(0.232)	
Mean IND9	1.354	***	1.361	***	1.366	***	1.364	***
	(0.236)		(0.236)		(0.238)		(0.238)	
Mean IND10	1.749	***	1.761	***	1.757	***	1.766	***
	(0.249)		(0.249)		(0.250)		(0.253)	
N	3,085		3,085		3,085		3,085	
Wald Chi	361		362		363		362	
Log likelihood	-1,542		-1,543		-1,541		-1,543	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. Robust and clustered standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively.

Table C 9: Estimation results of the Random Effects OLS using *1-PCM* (Continued from Table 3.4)

	Dependent variable: RD_{it}							
	I		II		III		IV	
YEAR1999[a]	-0.287	***	-0.284	***	-0.278	***	-0.285	***
	(0.064)		(0.065)		(0.064)		(0.065)	
YEAR2000[a]	-0.296	***	-0.300	***	-0.290	***	-0.299	***
	(0.087)		(0.087)		(0.087)		(0.086)	
YEAR2001[a]	-0.259	**	-0.261	**	-0.257	**	-0.263	**
	(0.109)		(0.109)		(0.108)		(0.109)	
YEAR2002[a]	0.042		0.041		0.021		0.041	
	(0.088)		(0.088)		(0.088)		(0.088)	
YEAR2003[a]	-0.022		-0.023		-0.040		-0.026	
	(0.091)		(0.091)		(0.091)		(0.091)	
YEAR2004[a]	-0.068		-0.070		-0.080		-0.076	
	(0.101)		(0.101)		(0.101)		(0.102)	
YEAR2005[a]	-0.133		-0.141		-0.157		-0.143	
	(0.116)		(0.116)		(0.116)		(0.116)	
Mean IND2	0.649		0.648		0.627		0.658	
	(0.438)		(0.440)		(0.454)		(0.445)	
Mean IND3	0.221		0.212		0.184		0.226	
	(0.435)		(0.437)		(0.451)		(0.443)	
Mean IND4	1.565	***	1.554	***	1.523	***	1.552	***
	(0.428)		(0.430)		(0.443)		(0.432)	
Mean IND5	0.541		0.526		0.496		0.537	
	(0.439)		(0.441)		(0.455)		(0.446)	
Mean IND6	0.281		0.261		0.262		0.270	
	(0.483)		(0.483)		(0.491)		(0.487)	
Mean IND7	0.395		0.389		0.343		0.406	
	(0.420)		(0.422)		(0.437)		(0.430)	
Mean IND8	1.359	***	1.359	***	1.329	***	1.372	***
	(0.432)		(0.435)		(0.449)		(0.440)	
Mean IND9	1.413	***	1.408	***	1.390	***	1.419	***
	(0.441)		(0.443)		(0.458)		(0.448)	
Mean IND10	2.154	***	2.141	***	2.105	***	2.158	***
	(0.428)		(0.430)		(0.445)		(0.437)	
N	1,954		1,954		1,954		1,954	
R^2	0.31		0.31		0.32		0.31	
P-value	0.000		0.000		0.000		0.000	

[a] Dummy variable. Robust and clustered standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively.

D Appendix: Selective search, sectoral patterns and the impact on product innovation performance

Table D 1: Descriptive statistics by type of knowledge search (Continued from Table 4.4)

	All firms		Science-driven search - above average use		Supplier-driven search - above average use		Market-driven search - above average use	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Share of sales with market novelties	0.102	0.181	0.112 ***	0.180	0.105	0.181	0.103	0.176
Share of sales with firm novelties	0.159	0.235	0.168 **	0.228	0.157	0.231	0.169 ***	0.230
Science-driven search (scale)	0.000	1.000	1.048 ***	0.800	0.037 ***	1.056	0.012	1.009
Supplier-driven search (scale)	0.000	1.000	0.126 ***	0.927	0.802 ***	0.543	0.003	0.934
Market-driven search (scale)	0.000	1.000	0.120 ***	0.940	0.033 **	0.984	0.815 ***	0.517
R&D intensity	0.024	0.083	0.039 ***	0.110	0.026 *	0.088	0.027 ***	0.084
Cont. R&D activities[a]	0.423	0.494	0.616 ***	0.486	0.452 ***	0.498	0.488 ***	0.500
Export intensity	0.212	0.280	0.267 ***	0.296	0.213	0.280	0.237 ***	0.284
Sales 1998 (log)	15.952	1.970	16.461 ***	2.073	15.993	1.952	16.137 ***	1.989
Part of company group[a]	0.458	0.498	0.551 ***	0.498	0.433 ***	0.496	0.483 ***	0.500
Process innovation[a]	0.647	0.478	0.692 ***	0.462	0.687 ***	0.464	0.641	0.480
Greece[a]	0.067	0.251	0.038 ***	0.192	0.071	0.257	0.049 ***	0.215
Portugal[a]	0.099	0.299	0.076 ***	0.265	0.105	0.307	0.080 ***	0.271
Spain[a]	0.412	0.492	0.420	0.494	0.393 ***	0.489	0.377 ***	0.485
Germany[a]	0.293	0.455	0.329 ***	0.470	0.311 ***	0.463	0.370 ***	0.483
Belgium[a]	0.129	0.335	0.136	0.343	0.119 **	0.324	0.125	0.331
Advanced knowledge	0.236	0.425	0.328 ***	0.470	0.238	0.426	0.271 ***	0.445
Mass production goods[a]	0.345	0.475	0.368 ***	0.482	0.339	0.474	0.361 **	0.480
Supporting infrastructure	0.162	0.369	0.100 ***	0.300	0.138 ***	0.345	0.155	0.362
Personal goods and services[a]	0.257	0.437	0.204 ***	0.403	0.285 ***	0.451	0.213 ***	0.409
N	4,933		1,932		2,522		2,535	

[a] Dummy variable. Standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively.

Table D 2: Results of Tobit estimations for the full sample (Continued from Table 4.5)

	Share of sales of market novelties I	Share of sales of firm novelties II
Greece[a]	-0.022	-0.070 ***
	(0.037)	(0.031)
Portugal[a]	0.109 ***	-0.081 ***
	(0.022)	(0.022)
Spain[a]	0.085 ***	0.109 ***
	(0.017)	(0.015)
Germany[a]	0.066 ***	0.058 ***
	(0.017)	(0.014)
Advanced knowledge providers[a]	0.028 **	0.031 *
	(0.014)	(0.016)
Mass production goods[a]	0.020	0.024 *
	(0.012)	(0.014)
Supporting infrastructure services[a]	0.003	0.011
	(0.016)	(0.017)
Wald-Test on joint significance of industry dummies	W(χ2(3)) = 4.99	W(χ2(3)) = 4.37
$R^2_{McFadden}$	0.14	0.12
N	4,933	4,933
LR/Wald chi2	306.82	288.90
P-value	0.00	0.00
Log likelihood	-1,872.29	-2,351.57
LR - Test on heteroscedasticity	LR(χ2(10)) = 3745***	LR(χ2(10)) = 4703***

[a] Dummy variable. Standard errors are shown in parentheses. Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***) respectively. Heteroscedasticity terms include 3 dummies for firm size measured by sales in 1998 (log) (0-24th percentile, 25th -49th percentile, 50th -74th percentile), country dummies and industry dummies.

Table D 3: Correlation matrix and variance inflation factors

		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
A	Science-driven search (scale)	1															
B	Supplier-driven search (scale)	0	1														
C	Market-driven search (scale)	0	0	1													
D	R&D intensity	0.218	0.019	0.041	1												
E	Continuous R&D activities[a]	0.325	0.054	0.164	0.263	1											
F	Export intensity	0.145	0.003	0.109	0.011	0.266	1										
G	Sales 1998 (log)	0.189	0.005	0.103	-0.109	0.285	0.279	1									
H	Part of company group[a]	0.156	-0.060	0.060	-0.007	0.191	0.179	0.478	1								
I	Process innovation[a]	0.063	0.119	-0.018	-0.030	0.081	0.060	0.148	0.068	1							
J	Greece[a]	-0.082	0.045	-0.097	-0.078	-0.094	-0.203	-0.184	-0.140	0.022	1						
K	Portugal[a]	-0.058	0.029	-0.089	-0.073	-0.111	0.048	-0.079	-0.039	0.100	-0.089	1					
L	Spain[a]	0.028	-0.060	-0.082	0.063	-0.006	-0.055	-0.039	-0.028	-0.067	-0.225	-0.277	1				
M	Germany[a]	0.049	0.042	0.219	-0.007	0.108	-0.042	0.180	0.035	0.005	-0.173	-0.214	-0.539	1			
N	Advanced knowledge providers[a]	0.194	-0.007	0.095	0.285	0.186	0.033	-0.151	-0.009	-0.073	-0.024	-0.106	-0.050	0.098	1		
O	Mass production goods[a]	0.032	-0.010	0.042	-0.059	0.099	0.187	0.079	0.051	0.026	-0.050	0.029	-0.011	-0.001	-0.403	1	
P	Supporting infrastructure services[a]	-0.140	-0.071	-0.014	-0.104	-0.185	-0.236	0.142	0.109	0.011	-0.008	-0.006	-0.111	0.101	-0.245	-0.319	1
VIF[b]		1.22	1.04	1.10	1.21	1.41	1.37	1.68	1.36	1.06	1.63	1.69	2.73	2.59	1.77	1.64	1.58
Mean VIF		1.57															
N		4,933															

[a] Dummy variable. [b] Variance Inflation Factor.

Eidesstattliche Versicherung

Hiermit erkläre ich an Eides statt, dass ich die Dissertation mit dem Titel „Vertical relationships, competition, knowledge search and innovation: Empirical evidence for German enterprises“ selbständig verfasst und alle in Anspruch genommenen Quellen und Hilfen in der Dissertation vermerkt habe. Die den herangezogenen Werken wörtlich oder sinngemäß entnommenen Stellen sind als solche gekennzeichnet.

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Mannheim, 03. 02. 2014 *Christian Köhler*